

**Annual Actuarial Review of  
The FHA Mutual Mortgage Insurance Fund  
Forward Loans  
Fiscal Year 2025**

Submitted to:



**United States Department of Housing  
and Urban Development**

Submitted by:



**IT Data Consulting, LLC (ITDC®)**  
12020 Sunrise Valley Dr., Suite #100  
Reston, VA 20191  
[www.it-dc.com](http://www.it-dc.com)  
[info@it-dc.com](mailto:info@it-dc.com)

December 11, 2025

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The Honorable Frank Cassidy  
Assistant Secretary for Housing and Federal Housing Commissioner  
U.S. Department of Housing and Urban Development (HUD)  
451 Seventh Street, S.W., Room 9100  
Washington, D.C. 20410

Dear Mr. Cassidy,

IT Data Consulting, LLC (ITDC) has finalized and is now submitting the Fiscal Year 2025 Independent Actuarial Review of the Single-Family Forward Mortgages under the Mutual Mortgage Insurance Fund, pursuant to contract number 86615723C00002.

This report is based on data as of September 30, 2025, providing an overview of the Economic Net Worth and details regarding the Cash Flow Net Present Value (NPV) for the Mutual Mortgage Insurance (MMI) Forward Loan portfolio as of the conclusion of Fiscal Year 2025. We've included a comparison with the corresponding estimate from the end of Fiscal Year 2024, evaluation under various scenarios, and offered detailed insights into the models employed for developing this estimate.

ITDC is here to answer any questions or address any comments you may have about the report and its conclusions.

Respectfully,



Benny Asnake  
President and CEO  
IT Data Consulting, LLC



December 11, 2025

The Honorable Frank Cassidy  
Assistant Secretary for Housing and Federal Housing Commissioner  
U.S. Department of Housing and Urban Development (HUD)  
451 Seventh Street, S.W., Room 9100  
Washington, D.C. 20410

Dear Mr. Cassidy,

I, Min Ji, am a Professor of Actuarial Science and Risk Management at Towson University. My research focuses on applying actuarial models to the risk management of insurance and financial products. I am a member of the American Academy of Actuaries (MAAA), a Fellow of the Society of Actuaries (FSA), and a Fellow of the Institute and Faculty of Actuaries (FIA). I serve on the Society of Actuaries' exam and research committees, keeping well connected to academia and the latest actuarial research in the insurance industry.

I meet the Qualification Standards for Actuaries Issuing Statements of Actuarial Opinion in the United States of the American Academy of Actuaries to render the actuarial opinion contained herein. I have reviewed the "*Annual Actuarial Review of The FHA Mutual Mortgage Insurance Fund, Forward Loans, for Fiscal Year 2025*". The purpose of my review was to determine the soundness of the methodology used, the appropriateness of the underlying assumptions applied, and the reasonableness of the resulting estimates derived in the Review.

The review was based upon data and information provided by the Federal Housing Administration (FHA). I have relied on FHA for the accuracy and completeness of this data. In addition, I also relied upon the reasonableness of the assumptions used in the economic projections from the FY 2026 Mid-Session Review of the President's Economic Assumptions (PEA).

It is my opinion that on an overall basis, the methodology and underlying assumptions used in the Review are reasonable and appropriate in the circumstances. In my opinion the estimates in the Review lie within a reasonable range of probable values as of this time although the actual experience in the future may not unfold as projected.

Respectfully,



Min Ji, Ph.D., MAAA, FSA, FIA

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## Summary of Deliverables

Below we summarize the findings associated with each of the required deliverables:

**Deliverable 1: Produce a written Actuarial Study for Forward that provides actuarial central estimates of Mutual Mortgage Insurance (MMI) Fund Economic Net Worth as of the end of Fiscal Year 2025 and assesses HUD’s estimates of Economic Net Worth.**

The Economic Net Worth is defined as cash available to the Fund plus the Net Present Value (NPV) of all future cash outflows and inflows that are expected to result from the mortgages currently insured by the Mutual Mortgage Insurance (MMI) Fund.

As of the end of 2025, ITDC’s Actuarial Central Estimate (ACE) of the MMI Forward Cash Flow NPV is positive \$ 37.164 billion.

The total capital resource as reported in the Annual Report to Congress regarding the status of the Federal Housing Administration (FHA) Mutual Mortgage Insurance Fund is a positive \$ 130.533 billion as of the end of Fiscal Year (FY) 2025. Thus, the estimated Economic Net Worth of the MMI is \$ 167.697 billion.

**Deliverable 2: Include a review of the risk characteristics of existing MMI loans including commentary on how such characteristics have changed in recent years.**

A review of the risk characteristics of existing MMI Forward loans and commentary on how these risk characteristics have changed is included in Section III, Characteristics of the 2025 Insurance Portfolio and Section I.C, FHA Policy Changes.

**Deliverable 3: Apply the final Forward actuarial model to the existing portfolio to produce conditional (and cumulative) claim, prepayment, and loss-given-default rates at various levels of aggregation across loans, and for individual policy years and policy year-quarter. Cash-flow summaries should also be provided for major categories (e.g., premium revenues, claim expenses and recoveries or net loss due to claims, with affected loan counts and balances).**

Models for projecting loan terminations and loan performance are described in Appendices B and G. Cash flow summaries by major category are displayed in the table below and discussed in more detail in Section II along with a detailed analysis of the cash flow calculations discussed in Appendix D.

Exhibit SD-1. Cash Flow Summary, 2025 (\$ Million)

| Cash Flow Category                | Net Present Value of Cash Flow |
|-----------------------------------|--------------------------------|
| Mortgage Insurance Annual Premium | \$ 72,846                      |
| Upfront Premium Refund            | \$ (1,050)                     |
| Loss Mitigation Expense           | \$ (12,317)                    |

| Cash Flow Category | Net Present Value of Cash Flow |
|--------------------|--------------------------------|
| Claim Expenses     | \$ (47,114)                    |
| Recoveries         | \$ 24,799                      |
| Net Present Value  | \$ 37,164                      |

**Deliverable 4: To promote transparency of the Studies’ assessments, the Studies should identify methodological vulnerabilities that may occur in its actuarial models or in HUD’s analyses of Economic Net Worth. This discussion should evaluate the scope and scale of such vulnerabilities in creating possible forecast risk and suggest possible lines of research in these areas. The Studies should assess and comment upon HUD’s own models that estimate Economic Net Worth for methodological vulnerabilities and compare HUD’s methodologies with those in the Studies.**

As part of the statutory actuarial review process, the results of review of HUD’s Forward and HECM models will be provided as an addendum to this report following its official publication. This addendum will include supplemental documentation and analysis that were not available at the time of release but are necessary to provide enhanced transparency and completeness of the actuarial review. The addendum will be published promptly upon finalization and will be considered an integral component of the actuarial review for the 2025 fiscal year. Appendix F of the study is a place holder for this assessment.

The assumptions and judgments underlying the ITDC Studies’ estimates are summarized in Appendices A through E of the report. Section IV provides a summary of the Net Present Value (NPV) calculations, which are based on simulated economic scenarios. We also discuss the economic conditions that could lead to materially adverse changes in the Cash Flow NPV.

We have examined the vulnerabilities of our studies and compared the results under various scenarios.

**Deliverable 5: The Studies should include historical data on changes in program terms as well as relevant loan and borrower characteristics (e.g., credit scores, loan-to-value ratios) by cohort and other sub-populations. Loan performance data (claim rates, prepayment rates, severity, and recovery rates) both historical and projected shall be presented in the “finger-table” formats (arrayed by cohort and policy years for different loan products).**

Section III, Characteristics of the Fiscal Year 2025 Insurance Portfolio, provides historical information on changes in the MMI programs. A review of the risk characteristics of existing MMI loans and commentary of how these risk characteristics have changed are included in Section I.C, FHA Policy Changes.

**Deliverable 6: The Contractor should use the FY 2026 Mid-Session Review of the President’s Economic Assumptions (PEA), provided by Office of Risk Management and Regulatory Affairs (ORMRA), for the actuarial central estimates of the Studies. However, in addition to**

**the central single path economic forecast, the Studies shall test alternative economic forecasts for stress-testing and sensitivity analysis to estimate ranges of reasonableness.**

ITDC has conducted a comprehensive analysis based on the President’s Economic Assumptions for Fiscal Year 2026 Mid-Session Review (PEA) provided by the Office of Management and Budget (OMB). Based on our assessment, the Cash Flow Net Present Value (NPV) by the conclusion of the 2025 fiscal year for cohort years 1995 to 2025 is a positive \$ 37.164 billion.

In the table below, we estimate that the range of Cash Flow NPV based on the pessimistic downside and optimistic upside stochastic simulation scenarios is between positive \$ 18.641 billion to positive \$ 47.200 billion. These two values from the optimistic upside and pessimistic downside are two extreme scenarios that are highly unlikely to occur. Our Baseline NPV of \$ 37.164 billion stays in the middle of \$ 42.712 billion from the moderate upside scenario and \$ 29.412 billion from the moderate downside scenario.

Exhibit SD-2. Net Present Value of the Forward Fund under Different Economic Scenarios (\$ Million)

| Economic Scenario                             | Fiscal Year 2025 Cash Flow NPV |
|-----------------------------------------------|--------------------------------|
| Baseline PEA                                  | \$ 37,164                      |
| Alternative 1 - Optimistic Upside Scenario    | \$ 47,200                      |
| Alternative 2 - Moderate Upside Scenario      | \$ 42,712                      |
| Alternative 3 - Moderate Downside Scenario    | \$ 29,412                      |
| Alternative 4 - Pessimistic Downside Scenario | \$ 18,641                      |

The Cash Flow NPV estimate provided by FHA to be used in the FHA Annual Report to Congress is positive \$ 42.872 billion. Based on ITDC’s actuarial central estimate utilizing the PEA and range of results from the stochastic simulation scenarios, we conclude that the FHA estimate of Cash Flow NPV is reasonable.

**Deliverable 7: To provide comparability to HUD estimates of Economic Net Worth, the Contractor shall use Federal Credit Reform Act discounting assumptions and procedures.**

The Executive Summary Section C, MMI Fund Performance Under Alternative Scenarios and Sensitivity Analysis, provides comparability to HUD estimates of Economic Net Worth and conforms to the Federal Credit Reform Act discounting assumptions and procedures.

**Deliverable 8: This Study should use stochastic or Monte Carlo simulations of future economic conditions including for interest rates and house price appreciation. The objective of these requirements is to illustrate the sensitivity of forecasts to economic uncertainty and other forms of forecast error.**

As described in Section IV, MMI Fund Performance Under Alternative Scenarios, and detailed in Appendix E: Stochastic Simulation Models, we generated different percentile economic scenarios using stochastic simulations.



**Deliverable 9: Provide econometric appendices to the Study that include variable specifications and statistical output from all regressions in the Studies.**

Appendices B, D, E and F include variable specifications and statistical output from all regressions in the Studies.

## Executive Summary

The Cranston-Gonzalez National Affordable Housing Act of 1990 (NAHA) requires an independent actuarial study of the economic worth of the Federal Housing Administration (FHA) and the Department of Housing and Urban Development's (HUD's) Mutual Mortgage Insurance (MMI) Fund. On July 30, 2008, the Housing and Economic Recovery Act of 2008 (HERA) transferred the obligation for an autonomous actuarial assessment to section 12 USC 1708(a)-(4).

HERA also restructured several supplementary programs under the purview of MMI. There are two MMI Funds: one for forward mortgages and one for reverse mortgages. The reverse mortgages are included under the Home Equity Conversion Mortgage (HECM) program, which is excluded from this report. In the remainder of this report, the term MMI refers to forward mortgages only.

The primary purpose of this analysis is to provide an updated estimate of the Economic Net Worth of the current mortgage portfolio as of 2025. Economic Net Worth is calculated by adding the available cash in the Fund to the Net Present Value (NPV) of all anticipated future cash flows from the mortgages currently insured by the MMI Fund.

ITDC has conducted a comprehensive analysis, utilizing economic forecasts from the OMB Economic Assumptions from the President's Economic Assumptions for Fiscal Year 2026 Mid-Session Review (PEA). Based on our assessment, the Cash Flow Net Present Value (NPV) by the conclusion of the cohort year from 1995 through 2025 is a positive \$ 37.164 billion. We also estimate that the range of Cash Flow NPV based on the pessimistic downside and optimistic upside stochastic simulation scenarios is between positive \$ 18.641 billion and \$ 47.200 billion.

### A. Status of the MMI Forward Portfolio

To assess the adequacy of the current and future capital resources to meet estimated future liabilities, ITDC analyzed all Single Family (SF) Forward defaults, claims, and associated recoveries using loan-level data reported by FHA through September 30, 2025. Based on historical experience, we developed loan level termination and cash flow models to estimate the future loan performance of the FY 1995 to FY 2025 books-of-business using various assumptions, including macroeconomic forecasts from the Office of Management and Budget (OMB), Moody's Analytics (Moody's), and the expected SF Forwards portfolio characteristics provided by FHA.

Using the macroeconomic inputs from the PEA regarding the future trajectory of home prices, mortgage interest rates, unemployment, the 1-year Constant Maturity Treasury (CMT) rate, and the 10-year Constant Maturity Treasury (CMT), ITDC projects the performance of the FY 1995 to 2025 books of SF Forwards loans, and estimates the SF Forwards Cash Flow Net Present Value (NPV) as of the end of FY 2025 is positive \$ 37.164 billion. The SF Forwards portion of total capital resource as reported in the Annual Report to Congress regarding the status of the FHA Mutual Mortgage Insurance (MMI) Fund is positive \$ 130.533 billion as of the end of FY 2025.

Thus, the estimated Economic Net Worth of the SF Forwards MMI Fund is positive \$ 167.697 billion.

ITDC also estimates that the Cash Flow NPV based on randomly generated economic scenarios is between positive \$ 18.641 billion to positive \$ 47.200 billion. These two values from the optimistic upside and pessimistic downside are two extreme scenarios that are unlikely to occur. Our Baseline PEA NPV of \$ 37.164 billion stays in the middle of \$ 42.712 billion from the moderate upside scenario and \$ 29.412 billion from the moderate downside scenario.

The Cash Flow NPV estimate provided by FHA to be used in the FHA Annual Report to Congress is a positive \$ 42.872 billion. Based on ITDC's actuarial central estimate utilizing the baseline PEA and range of results from the stochastic simulation scenarios, we conclude that the FHA estimate of Cash Flow NPV is reasonable.

The insurance-in-force (IIF) is calculated as the total Unpaid Principal Balance (UPB) of all SF Forwards loans remaining in the insurance portfolio as of September 30, 2025. New endorsements in 2025 are added to the portfolio and the SF Forwards IIF as of the end of FY 2025 is \$201.509 billion. Exhibit ES-1 provides Actuarial Central Estimate (ACE), unamortized IIF and amortized IIF of the SF Forwards portfolio for FY 1995 through FY 2025.

Exhibit ES-1. Projected MMI Forward Performance for 2025 (\$ Million)

| Cohort Years | Cash Flow NPV | Unamortized Insurance-in-Force | Amortized Insurance-in-Force |
|--------------|---------------|--------------------------------|------------------------------|
| 1995-2025    | \$ 37,164     | \$ 1,795,689                   | \$ 1,582,946                 |

## B. Sources of Change in the Status of the Forward Portfolio

The FY 2024 Forward Review reported that the economic net worth of the SF Forward portfolio was \$153.9 billion at the conclusion of 2024, contrasting with this review, which estimates a positive value of \$ 167.697 billion at the end of 2025. Exhibit ES-2 compares our MMI Cash Flow NPV and IIF estimate for 2025 to the estimates in the 2024 Review.

Exhibit ES-2. Estimate of Cash Flow NPV as of 2025 (\$ Million)

| Item              | Cash Flow NPV | Capital Resources | Unamortized Insurance-In-Force (IIF) |
|-------------------|---------------|-------------------|--------------------------------------|
| 2024              | \$ 38,016     | \$ 115,853        | \$ 1,632,547                         |
| 2025              | \$ 37,164     | \$ 130,533        | \$ 1,795,689                         |
| Dollar Difference | \$ (852)      | \$ 14,681         | \$ 163,142                           |
| Percent Change    | -2.24%        | 12.67%            | 9.99%                                |

As seen in Exhibit ES-2, the Forward portion of the MMI Fund's estimated 2025 Cash Flow NPV has decreased by \$ 852 million from the level estimated in Fiscal Year 2024, from positive \$38.016 billion to positive \$37.164 billion. The capital resources available to the MMI Fund have increased

by 12.67 percent, from \$115.853 billion to positive \$ 130.533 billion. The unamortized IIF increased by 9.99 percent from \$1.633 trillion to \$ 1.796 trillion.

### C. Impact of Economic Forecasts:

The Fund's economic net worth for 2025 will depend on the economic conditions expected to prevail over the next 30 years and, most critically, during the next 10 years. We have captured the most significant factors in the U.S. economy affecting the performance of the loans insured by the Fund using the following variables in our models:

- 30-year, 15-year, and adjustable-rate mortgage rates
- 1-year and 10-year constant maturity Treasury rates
- National and local house price indices
- National and local unemployment rates

The projected performance of FHA's current book of business, as measured by economic net worth, depends on future forecasts of these economic drivers. The baseline scenario for the primary economic drivers was developed consistently with the PEA. The PEA is published by the Office of Management and Budget in compliance with the requirements of the Federal Credit Reform Act.

Our primary source of historical data on these economic factors is Moody's Economy.com, a leading provider of economic research and data. Moody's has developed data from original sources, including the Federal Reserve, Bureau of Labor Statistics, Bureau of the Census, Bureau of Economic Analysis, Federal Housing Finance Agency, The Conference Board, Dow Jones, National Association of Realtors, and Freddie Mac. Depending on the data series, information is provided at the national, state, county, metropolitan area, and ZIP code level. Moody's data are combined with historical loan-level data from HUD's Single-Family Data Warehouse (SFDW) to build out loan-level panel data and event histories (defaults, cures, claims, prepayments) for use in estimating statistical models of loan performance. The estimated loan performance models are then combined with the forecasts of economic drivers based on the PEA to produce our baseline forecast.

In addition to the mandated baseline PEA forecasts, we apply four alternative stochastic simulation scenarios of potential random deviations from the PEA baseline. To summarize the five scenarios for which we report estimates of economic net worth:

- Baseline – Published PEA
- Alternative 1 – Optimistic Upside Scenario
- Alternative 2 – Moderate Upside Scenario

- Alternative 3 – Moderate Downside Scenario
- Alternative 4 – Pessimistic Downside Scenario

Each of these scenarios is based on combinations of selected “percentile” paths for the economic drivers that correspond to favorable or unfavorable outcomes for the prospects of the Single Family MMI Fund portfolio. Rising interest rates, rising housing values, and declining unemployment rates are favorable outcomes, because they lead to lower prepayments (increasing future premium income) and lower default, claim, and loss rates (reducing future losses). Conversely, declining interest rates, falling house prices, and rising unemployment rates are unfavorable outcomes, because they lead to higher prepayment rates (lowering future premium income) and higher default and claim rates (increasing future losses). Some elements of our more optimistic scenarios, such as higher interest rates, may not conform to the usual interpretation of favorable economic conditions, but are in fact favorable to the current economic net worth of the MMI Fund.

The combinations of selected percentile paths comprising each of the alternative scenarios described above are summarized here:

Alternative 1 – Optimistic Upside Scenario

Treasury and Mortgage Rates: 90<sup>th</sup> percentile

Unemployment Rate: 10<sup>th</sup> percentile

House Price Appreciation Rate: 90<sup>th</sup> percentile

Alternative 2 – Moderate Upside Scenario

Treasury and Mortgage Rates: 75<sup>th</sup> percentile

Unemployment Rate: 25<sup>th</sup> percentile

House Price Appreciation Rate: 75<sup>th</sup> percentile

Alternative 3 – Moderate Downside Scenario

Treasury and Mortgage Rates: 25<sup>th</sup> percentile

Unemployment Rate: 75<sup>th</sup> percentile

House Price Appreciation Rate: 25<sup>th</sup> percentile

Alternative 4 – Pessimistic Downside Scenario

Treasury and Mortgage Rates: 10<sup>th</sup> percentile

Unemployment Rate: 90<sup>th</sup> percentile

House Price Appreciation Rate: 10<sup>th</sup> percentile

The PEA forecast developed by OMB does not cover all the economy drivers that are included in our models. Additional economic variables that must be forecast, such as Fixed Rate Mortgage (FRM) 15-Year and Adjustable-Rate Mortgage (ARM) origination rates, regional and local house price indices, and unemployment rates, are developed using the PEA and additional data from Moody's. The forecasts for all additional series are driven by the corresponding national PEA forecasts. Additional details may be found in the discussion of stochastic simulation models in Appendix E.

Exhibit ES-3 presents the actuarial central estimate of the cash flow NPV from the projections based on the PEA and four alternative scenarios. The actuarial central estimate uses the PEA for FY 2026 published by the Office of Management and Budget, in compliance with the requirements of Federal Credit Reform Act. Four alternative scenarios represent different percentile paths of interest rates and the House Price Index (HPI) from 1000 simulations.

Stochastic scenarios are simulated using the best fitted GARCH model with mean replaced by the corresponding PEA, to ensure the simulated paths will not drift far away from the PEA while having stochastic volatilities.

Exhibit ES-3. Range of Cash Flow NPV Outcomes Based on Stochastic Simulations (\$ Million)

| Economic Scenario                             | Fiscal Year 2025 Cash Flow NPV* |
|-----------------------------------------------|---------------------------------|
| Baseline**                                    | \$ 37,164                       |
| Alternative 1 - Optimistic Upside Scenario*** | \$ 47,200                       |
| Alternative 2 - Moderate Upside Scenario      | \$ 42,712                       |
| Alternative 3 - Moderate Downside Scenario    | \$ 29,412                       |
| Alternative 4 - Pessimistic Downside Scenario | \$ 18,641                       |

*\*All values are expressed as of the end of the fiscal year period*

*\*\*Baseline is based on PEA*

*\*\*\* Description of these scenarios are found in Section IV and Appendix E*

Our baseline PEA Cash Flow NPV of \$ 37.164 billion stays in the middle of the \$ 29.412 billion moderate downside scenario and the \$ 42.712 billion moderate upside scenario. The range of Cash Flow NPV based on the more extreme scenarios range from \$ 18.641 billion from Alternative 4 – Pessimistic Downside Scenario to \$ 47.200 billion from Alternative 1 – Optimistic Upside Scenario. These two values from the optimistic upside and pessimistic downside are two extreme scenarios that are unlikely to occur.

The 2025 Cash Flow NPV estimate provided by FHA is positive \$ 42.872 billion. Based on ITDC's Cash Flow NPV estimate utilizing the Baseline PEA and range of results from the stochastic simulation scenarios, we conclude that the FHA estimate of Cash Flow NPV is reasonable.

## Distribution and Use

ITDC provides this report to the FHA and policymakers for their assessment of the Economic Net Worth of the MMI Fund. Our conclusions are based on various assumptions about future conditions and events, detailed in subsequent sections of this report. These assumptions must be comprehended to contextualize our conclusions properly. Furthermore, our work is subject to inherent limitations, also discussed in this report.

The distribution of this report is allowed on the condition that it is shared in its entirety, including all exhibits and appendices, without any excerpts. ITDC acknowledges that FHA will integrate this report into its Annual Report to Congress, and ITDC grants permission for this purpose. We are available to address any questions that may arise concerning this report.

Any third party receiving this report should understand that its provision does not replace their responsibility to conduct due diligence. They should not place reliance on this report or its enclosed data to establish any explicit or implicit representations, warranties, duties, or liabilities from ITDC to the third party.

## I. Introduction

### A. Actuarial Reviews of the FHA Mutual Mortgage Insurance Fund

The National Housing Act requires an annual independent actuarial review of the Federal Housing Administration's (FHA) Mutual Mortgage Insurance (MMI) Fund.<sup>1</sup> ITDC was engaged by the Department of Housing and Urban Development (HUD) to conduct an independent actuarial review of the MMI Fund for 2025. This study is required by 12 USC 1708(a)-(4) and must be completed in compliance with the Federal Credit Reform Act as implemented and all applicable Actuarial Standards of Practice (ASOPs) promulgated by the Actuarial Standards Board of the American Academy of Actuaries. This study analyzes the financial position of the MMI Fund for 2025 using data through September 30, 2025.

The MMI Fund is a group of accounts of the federal government that records transactions associated with the FHA's guarantee programs for single-family mortgages. Currently, the FHA insures approximately 8 million forward mortgages under the MMI Fund.

Per 12 USC 1711-(f), FHA must ensure that the MMI Fund maintains a capital ratio of not less than 2.0 percent. The capital ratio is the ratio of capital to the MMI Fund's obligations on outstanding mortgages, known as Insurance in Force (IIF). Capital is defined as cash available to the Fund plus the Net Present Value (NPV) of all future cash outflows and inflows expected to result from the mortgages currently insured by the MMI Fund.

### B. Forward Program Overview

#### i. Products

FHA mortgage insurance is available for all the most utilized mortgage products including long-term (typically 30-year) fixed rate loans, intermediate-term fixed rate loans, and adjustable-rate loans for both home purchase and to refinance existing mortgage debt. Under Section 203(b) program, insurance is available on one-to-four-unit homes including eligible manufactured homes and individual condominium units. The Section 203(k) program supports financing for rehabilitation costs in addition to property acquisition or refinancing needs. FHA offers a "streamline refinance" program supporting refinancing of existing FHA-insured mortgages requiring only limited borrower credit documentation and underwriting.

#### ii. Premiums and claims

Premium income is collected both at time of loan origination and annually over the life of each loan. FHA draws on this premium income to pay out mortgage insurance claims in the event of a defaulted loan termination.

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<sup>1</sup> HERA moved the requirement from the 1990 National Affordable Housing Act (NAHA) to the Federal Housing Administration operations within the National Housing Act, 12 USC 1708(a)(4).



### iii. Delinquencies

FHA's guarantee of payment to lenders in the event of default facilitates lending to borrowers who might otherwise not be able to access mortgage credit. As an illustration, average FHA credit score for loans insured during fiscal 2024, excluding streamline refinances, was 677, as compared with an average score of 753 on the Fannie Mae book of business as of the 2024 calendar-year-end.<sup>2</sup> In view of these differences, it should not come as a surprise that FHA 90-day delinquency rates of 3.9% as of February 2025 exceed those of Fannie Mae, which was 0.6% as of that date.<sup>3</sup>

### iv. Loss Mitigation

FHA offers a wide range of loss mitigation options designed to assist FHA-insured homeowners facing financial hardship. These include forbearance programs to temporarily pause or reduce monthly payments, loan modifications adding arrearages to principal loan balance and extending repayment term, and partial claims placing arrearages in a zero-interest subordinate lien against the collateral property. If the mortgage cannot be reinstated by the aforementioned options, terminating through pre-foreclosure sales and deed-in-lieu of foreclosure are the final options in the loss mitigation program.<sup>4</sup> See Section I.C for discussion of recent mortgagee letters pertaining to loss mitigation.

### v. Loan Terminations

An FHA loan terminates upon maturity, refinancing, or through mortgage defaults resulting in foreclosure, pre-foreclosure sale, or deed-in-lieu of foreclosure.

### vi. Conveyance and Recoveries

"Conveyance" refers to the process where a lender transfers a defaulted loan to FHA upon filing a claim. In such cases, FHA may recover a portion of the claim via foreclosure proceeds or through sale of property acquired via deed-in-lieu of foreclosure.

### vii. Prepayments

Loan prepayment is when a borrower pays back all or part of a loan's outstanding balance before the scheduled due date. In this report, prepayment is referred to as "complete prepayment" in which case the loan is terminated after full payment of the outstanding balance.

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<sup>2</sup> FHA [Annual Management Report Fiscal Year 2024](#); [Fannie Mae Financial Supplement Q4 and Full Year 2024](#).

<sup>3</sup> [FHA Single Family Loan Performance Trends February 2025 Credit Risk Report](#); [Fannie Mae Monthly Summary, February 2025](#).

<sup>4</sup> <https://www.hud.gov/helping-americans/fha-loss-mitigation>.

## C. FHA Policy Changes and Recent Mortgagee Letters

Since the mid-1990s, the Federal Housing Administration (FHA) has enacted numerous policy adjustments that have had a notable impact on the financial health of the Mutual Mortgage Insurance (MMI) Fund. Essential modifications encompass revised underwriting guidelines, changes in homeownership counseling prerequisites, the adoption of automated underwriting systems, alterations to mortgage insurance premium structures, downpayment assistance and closing costs, along with the introduction of programs dedicated to foreclosure avoidance and loss mitigation and COVID-19. The following summarizes each of these significant developments.

### i. Revised Underwriting Guidelines and Other Policy Issues

In 1995, the FHA implemented a series of alterations to their underwriting guidelines to remove needless obstacles to homeownership. These changes were designed to offer more flexibility in evaluating the creditworthiness of nontraditional and underserved borrowers while also providing more explicit guidance to prevent discriminatory application of underwriting requirements. While these adjustments did expand homeownership opportunities for many households, the more lenient underwriting standards also played a role in the subsequent rise in FHA claim rates for loans that originated after 1995.

In 1998, modifications were introduced to the underwriting guidelines governing adjustable-rate mortgages (ARMs) in response to the elevated loss rates that the FHA encountered with these loans. An in-depth study of ARM claim rates by the FHA revealed the necessity for credit policy changes to uphold the MMI Fund's actuarial stability. Consequently, because of these adjustments, ARM applicants were mandated to qualify based on a mortgage payment amount calculated using the highest potential second-year interest rate. Additionally, any temporary interest rate reduction method for ARMs could no longer be applied to establish qualifying payment ratios.

In 2008, HERA set the minimum borrower cash equity requirement to 3.5 percent for purchase loans.<sup>5</sup> FHA also established a minimum FICO score of 500 for loans with 90 percent or higher loan-to-value ratios (LTVs). This rule was further tightened in 2010.<sup>6</sup> Starting October 4, 2010, borrowers with credit scores below 500 were no longer eligible for FHA insurance, and the maximum loan-to-value ratio for borrowers with credit scores between 500 and 579 was limited to 90 percent. In 2011, FHA removed eligibility for loans on investor property.<sup>7</sup> In 2012, the FHA modified documentation requirements for self-employed borrowers. Starting April 1, 2012, profit-loss and balance sheets of self-employed borrowers have been required in most cases.<sup>8</sup> Also, for identity-of-interest transactions, the family member definition was expanded to include the extended family, including brothers, sisters, uncles, and aunts.

<sup>5</sup> Mortgagee Letter 2008-23, September 5, 2008: Revised Downpayment and Maximum Mortgage Requirements.

<sup>6</sup> Mortgagee Letter 2010-29, September 3, 2010: Minimum Credit Scores and Loan-to-Value Ratios.

<sup>7</sup> HUD 4155.1, Section B. Property Ownership Requirements and Restrictions. 4155.1 4.B.1.a: Occupancy Restrictions.

<sup>8</sup> Mortgagee Letter 2012-03, February 28, 2012: Miscellaneous Underwriting Issues.

For manually underwritten loans assigned on or after April 21, 2014, HUD clarified a series of maximum qualifying ratios for different lowest minimum decision credit scores and acceptable compensating factors.<sup>9</sup> It also revised the compensating factors that must be cited to exceed FHA's standard qualifying ratios for manually underwritten loans.

## ii. Changes to Homeownership Counseling Prerequisites

The FHA has historically promoted homebuyer counseling on the premise that educating prospective homeowners about homeownership and mortgage matters would decrease the likelihood of mortgage defaults and foster a more responsible approach to homeownership. The following provides an overview of the history of mortgagee letters about homebuyer counseling.

- In 1993 a pilot counseling program for pre-purchase and pre-foreclosure situations was announced.<sup>10</sup>
- In 1996, after the pilot counseling program, the upfront Mortgage Insurance Premium (MIP) was decreased by 25 basis points for first-time homebuyers who completed homeownership counseling.<sup>11</sup> One year later, in 1997, the upfront MIP further decreased by another 25 basis points for first-time homebuyers who completed homeownership counseling.<sup>12</sup> This discount was provided to recognize the expected improvement in default experience.
- In 1998, a mortgagee letter was released indicating that the homeownership counseling program would be reviewed. This was in response to homeownership counseling programs that were being used that did not meet FHA guidelines. While the counseling program required that it should involve 15 to 20 hours of instruction, there were cases where homebuyers were provided with workbooks without additional interaction or instruction. The guidelines of the homeownership counseling program were reiterated in this letter.<sup>13</sup>
- In 2000, in conjunction with an overall reduction in upfront MIP, the homeownership counseling discount was discontinued.<sup>14</sup>

<sup>9</sup> Mortgagee Letter 2014-02, January 21, 2014: Manual Underwriting.

<sup>10</sup> Mortgagee Letter 93-28, September 20, 1993: Prepurchase and Foreclosure Prevention Counseling Demonstration.

<sup>11</sup> Mortgagee Letter 96-48, August 28, 1996: Single Family Production - Reduction in Up-Front Mortgage Insurance Premiums (UFMIP) for First-Time Homebuyers Who Receive Housing Counseling.

<sup>12</sup> Mortgagee Letter 97-37, August 13, 1997: Single Family Production - Further Reduction in Up-Front Mortgage Insurance Premiums (UFMIP) for First-Time Homebuyers Who Receive Housing Counseling

<sup>13</sup> Mortgagee Letter 98-1, January 2, 1998: Single Family Loan Production - Underwriting Adjustable Rate Mortgages, Interest Buydowns, Homeownership Counseling and Other Credit Policy Issues.

<sup>14</sup> Mortgagee Letter 2000-38, October 27, 2000: Single Family Loan Production - Further Reduction in Upfront Mortgage Insurance Premiums and Other Mortgage Insurance Premium Changes

### iii. Adoption of Automated Underwriting Systems

Beginning in 1995, automated underwriting systems (AUSs) began to increase. Theoretically, using AUSs increases the availability of mortgages and improves the efficiency and speed of mortgage processing. The following are key events in the history of AUS:

- In 1995, HUD approved the usage of AUSs. Mortgagors had to request permission to use these systems and receive approval from HUD.<sup>15</sup>
- In 1996, criteria were established for the approval of AUSs by HUD.<sup>16</sup>
- In 1998, the FHA approved using Freddie Mac's Loan Prospector in underwriting FHA-insured mortgages. A specific scorecard tailored for FHA-endorsed loans was introduced. Additionally, FHA made significant alterations to its credit policies and lessened documentation prerequisites for loans assessed by the Loan Prospector. This marked the inaugural inclusion of an Automated Underwriting System (AUS) in FHA's insurance endorsement process.
- In 1999, Fannie Mae's Desktop Underwriter and PMI Mortgage Services' Automated Underwriting Risk Analysis (AURA) systems received approval for underwriting FHA mortgages. Approval was followed by Countrywide Funding Corporation's Countrywide Loan-Underwriting Expert System (CLUES) and JP Morgan-Chase's Zippy shortly after that.
- Starting in May 2004, all approved AUSs applied FHA's Technology-Open-To-Approved-Lenders (TOTAL) mortgage scorecard to assess loan applications for potential automated approval for FHA insurance. Initially, over two-thirds of submitted loans typically received automated approval, eliminating the need for manual underwriting reviews. Since May 2004, HUD has mandated lenders to provide borrower credit scores.

### iv. Alteration in Mortgage Insurance Premium Structures

Sufficient Mortgage Insurance Premium (MIP) plays a pivotal role in upholding the financial stability of the MMI Fund. However, the MIP rate can also influence the affordability of homes for prospective buyers. The following provides a summary of the changes in MIP since 1991.

- In 1991, FHA decided to calculate the Mortgage Insurance Premium (MIP) as a combination of an upfront MIP and an annual premium, with the latter being a percentage of the remaining outstanding mortgage balance each year.<sup>17</sup> This adjustment led to an

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<sup>15</sup> Mortgagee Letter 95-7, January 27, 1995: Single Family Loan Production - Revised Underwriting Guidelines and Other Policy Issues

<sup>16</sup> Mortgagee Letter 96-34, July 10, 1996: Single Family Loan Production - Automated Underwriting Systems.

<sup>17</sup> Mortgagee Letter 91-26, May 30, 1991: Single Family Insurance Processing for Risk Based Insurance Premiums.

overall increase in MIP, which was necessary to fulfill the new capital requirement by NAHA.

- In 1994, the upfront MIP decreased by 75 basis points to 2.25 percent.<sup>18</sup> This was in response to the improved financial experience of the MMI Fund.
- In 1996, the upfront MIP decreased by 25 basis points to 2.00 percent for first-time homebuyers who received mortgage counseling before purchasing their home.<sup>19</sup> This was implemented based on the pilot program's success, which showed that first-time homebuyers who received this counseling had better default experiences.
- In 1997, the upfront MIP was decreased by an additional 25 basis points to 1.75 percent for first-time homebuyers who received mortgage counseling before purchasing their home. The upfront MIP was 50 basis points lower than it would be for a homebuyer who did not receive counseling.<sup>20</sup>
- In 2000, several changes were implemented in recognition of the improved experience of the MMI Fund. First, the upfront MIP was reduced by 75 basis points to 1.50 percent. Second, the upfront MIP refund schedule was shortened to five years instead of seven. Third, a provision to cancel the annual MIP once the loan-to-value (LTV) ratio was 78 percent or less was implemented. Also, the discount in the upfront MIP for first-time homebuyers who received counseling was discontinued.<sup>21</sup>
- In April 2010, upfront MIP was increased by 75 basis points to 2.25 percent.<sup>22</sup> This premium increase was in response to the housing and economic crisis in 2008 and was the first in a series of increases over the next three years.
- In October of 2010, upfront MIP decreased, but annual MIP increased significantly.<sup>23</sup> Overall, this increased MIP.
- In 2011, the annual MIP was increased by 25 basis points.<sup>24</sup>

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<sup>18</sup> Mortgagee Letter 94-14, March 31, 1994: Single Family Loan Production – Reduced Upfront Mortgage Insurance Premium (UFMIP).

<sup>19</sup> Mortgagee Letter 96-48, August 28, 1996: Single Family Production – Reduction in Up-Front Mortgage Insurance Premiums (UFMIP) for First-Time Homebuyers Who Receive Housing Counseling.

<sup>20</sup> Mortgagee Letter 97-37, August 13, 1997: Single Family Production – Further Reduction in Up-Front Mortgage Insurance Premiums (UFMIP) for First-Time Homebuyers Who Receive Housing Counseling.

<sup>21</sup> Mortgagee Letter 2000-38, October 27, 2000: Single Family Loan Production – Further Reduction in Upfront Mortgage Insurance Premiums and Other Mortgage Insurance Premium Changes.

<sup>22</sup> Mortgagee Letter 2010-02, January 21, 2010: Increase in Upfront Premiums for FHA Mortgage Insurance.

<sup>23</sup> Mortgagee Letter 2010-28, September 1, 2010: Changes to FHA Mortgage Insurance Premiums.

<sup>24</sup> Mortgagee Letter 2011-10, February 14, 2011: Annual Mortgage Insurance Premium Changes and Guidance on Case Numbers.

- In 2012, the annual MIP was increased by ten basis points.<sup>25</sup>
- In 2013, several changes were implemented related to the annual MIP. First, the term for collection of MIPs was extended to 11 years for mortgages with an initial LTV ratio of 90 percent or less and 30 years for mortgages with an initial LTV ratio greater than 90 percent. Second, mortgages with terms of 15 years or less and an LTV ratio of 78 percent or less at the time of origination, which were exempt from MIP, would no longer be exempt. Lastly, the annual MIP was increased by 5 to 10 basis points for mortgages with terms of 15 years or less and LTV ratios of 78 percent or less at origination.<sup>26</sup>
- As a result of improved financial experience, in 2015, annual MIP rates were decreased by 50 basis points for loans with terms greater than 15 years.<sup>27</sup>
- In 2017, a decrease was proposed for annual MIP rates,<sup>28</sup> but this decrease was suspended later in the year.<sup>29</sup>
- In 2023, FHA determined that a reduction in the annual MIP rate was necessary and appropriate to execute FHA's mission and role in the mortgage market. This resulted in a 30-basis point decrease in the annual MIP rate across most programs.<sup>30</sup>

#### v. Downpayment Assistance and Closing Costs

The origin of funds for down payments and closing costs has been a significant concern for HUD. Regulations limit the amount of assistance from sources other than the borrower or their family, and HUD has issued numerous mortgagee letters to address this matter. While aiding down payments and closing costs expand homeownership opportunities, it is worth noting that historically, mortgages with a larger share of these expenses covered by external sources have shown poorer performance. The following section summarizes the mortgagee letters addressing this issue.

- Before 1992, closing costs could not be financed as part of the loan. In 1992, the limitation on financing closing costs was removed, but mortgages were still subject to LTV ratio

<sup>25</sup> Mortgagee Letter 2012-04, March 6, 2012: Single Family Mortgage Insurance: Annual and Up-Front Mortgage Insurance Premium – Changes.

<sup>26</sup> Mortgagee Letter 2013-04, January 31, 2013: Revision of Federal Housing Administration (FHA) policies concerning cancellation of the annual Mortgage Insurance Premium (MIP) and increase to the annual MIP.

<sup>27</sup> Mortgagee Letter 2015-01, January 9, 2015: Reduction of Federal Housing Administration (FHA) annual Mortgage Insurance Premium (MIP) rates and Temporary Case Cancellation Authority.

<sup>28</sup> Mortgagee Letter 2017-01, January 9, 2017: Reduction of Federal Housing Administration (FHA) Annual Mortgage Insurance Premium (MIP) Rates.

<sup>29</sup> Mortgagee Letter 2017-07, January 20, 2017: Suspension of Mortgagee Letter 2017-01 – Reduction of Federal Housing Administration (FHA) Annual Mortgage Insurance Premium (MIP) Rates.

<sup>30</sup> Mortgagee Letter 2023-05, February 22, 2023: Reduction of Federal Housing Administration (FHA) Annual Mortgage Insurance Premium (MIP) Rate.



limits.<sup>31</sup> This provision was implemented to make it easier for homebuyers to meet the down payment requirements.

- In 1996, HUD allowed family members to lend the borrower 100 percent of the down payment.<sup>32</sup> This also was intended to make it easier for individuals and families to achieve homeownership.
- Two provisions were implemented in 1998. First, it was prohibited for the seller or any other party to pay mortgage interest for the buyer. In addition, any interest rate buydown could not result in a lower interest rate of more than 2 percent below the note rate. These changes were implemented to avoid a significant increase in the payment amount once the seller-paid mortgage interest funds were depleted or the interest rate buydown term was complete.<sup>33</sup>
- In 2000, HUD guided mortgages to ensure that the source of gifts to buyers is documented, and the person giving the gift must certify that the funds did not come from someone with an interest in the transaction. This was implemented to combat a practice of the sellers providing funds to family members of the buyer that would then be used for the down payment.<sup>34</sup>
- Section 2113 of the Housing and Economic Recovery Act of 2008 prohibited down payment contributions from a seller or any other person or entity that would financially benefit from the transaction.<sup>35</sup>
- In 2019, guidance by HUD was provided to clarify the rules associated with funds being provided by a governmental source for down payment assistance. The mortgagee letter requires the mortgagee to verify that the funds provided by the government agency were transferred to the Borrower before or at the time of closing and that the governmental agency was acting in its legal capacity in providing these funds. Documentation is also required by the government that the agency has the authority to provide the funds and from an attorney for the government entity verifying that the property is within the government agency's jurisdiction. There can be no direct transfer of assistance from the government agency to the mortgagee, and there can be no requirement that the loan be transferred to a

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<sup>31</sup> Mortgagee Letter 92-39, October 16, 1992: Single Family Loan Production - Elimination of Limit on Financing Closing Costs.

<sup>32</sup> Mortgagee Letter 96-58, October 23, 1996: Single Family Loan Production - Secondary Financing from Family Members.

<sup>33</sup> Mortgagee Letter 98-1, January 2, 1998: Single Family Loan Production - Underwriting Adjustable Rate Mortgages, Interest Buydowns, Homeownership Counseling and Other Credit Policy Issues

<sup>34</sup> Mortgagee Letter 2000-28, August 7, 2000: Gift Documentation, Mortgage Forms and other Credit Policy and Appraisal Issues.

<sup>35</sup> <https://www.congress.gov/110/plaws/publ289/PLAW-110publ289.pdf>

specific mortgage as a condition of receiving assistance from the government agency.<sup>36</sup> This guidance was subsequently suspended until further notice and ultimately rescinded.<sup>37</sup>

## vi. Foreclosure Avoidance and Loss Mitigation Programs

The pre-foreclosure sale (PFS) program allows mortgagors to sell their homes and use the proceeds to satisfy their mortgage debt obligations even if the proceeds were less than owed. Ultimately, these programs help limit the number of defaults that turn into claims and limit the losses sustained by the MMI Fund when a claim occurs. There are also certain situations where HUD can pursue a deficiency judgment against the borrower if their PFS amount does not cover the mortgage balance if it is consistent with state law.

Over the years, FHA has issued many mortgagee letters related to foreclosure and loss mitigation:

- In 1996, a mortgagee letter was released to provide information on the loss mitigation procedures, including unique forbearance plans, mortgage modifications, PFSs, deeds instead of foreclosure, and partial claims. The primary objective was to keep the homeowner in the home, and if that was not possible, then the objective was the disposition of the property without full foreclosure.<sup>38</sup>
- In 2008, due to the increase in defaults resulting from the housing crisis, FHA released a mortgagee letter reminding mortgagees of PFS as an option and consolidated the provisions of the PFS program into one place. This letter also updated the provisions of the PFS to address the mortgage crisis better.<sup>39</sup>
- In 2010, FHA released a mortgagee letter announcing enhancements to the FHA refinance program to allow responsible borrowers an opportunity to stay in their homes. This could occur if the lender agreed to write off at least 10 percent of the principal balance and if the remaining loan provisions were met.<sup>40</sup>
- In 2011, FHA issued guidance requiring a trial payment program before completing a permanent loan modification or partial claim. During the trial payment period, the borrower must complete three months of payments at the amount that will continue under the modification.<sup>41</sup>

<sup>36</sup> Mortgagee Letter 19-06, April 18, 2019: Downpayment Assistance and Operating in a Governmental Capacity.

<sup>37</sup> Mortgagee Letter 19-12, August 13, 2019: Rescission of Mortgagee Letters 2019-06, Downpayment Assistance And Operating in a Governmental Capacity; 2019-07, Extension of the Effective Date of Mortgagee Letter 2019-06, Downpayment Assistance and Operating in a Governmental Capacity; and 2019-10, Suspension of the Effective Date of Mortgagee Letter 2019-06, Downpayment Assistance and Operating in a Governmental Capacity.

<sup>38</sup> Mortgagee Letter 96-61, November 12, 1996: FHA Loss Mitigation Procedures - Special Instructions.

<sup>39</sup> Mortgagee Letter 2008-43, December 24, 2008: Pre-Foreclosure Sale (PFS) Program - Utilizing the PFS Loss Mitigation Option to Assist Families Facing Foreclosure.

<sup>40</sup> Mortgagee Letter 2010-23, August 6, 2010: FHA Refinance of Borrowers in Negative Equity Positions.

<sup>41</sup> Mortgagee Letter 2011-28, August 15, 2011: Trial Payment Plan for Loan Modifications and Partial Claims under Federal Housing Administration's Loss Mitigation Program.



- In 2012, FHA revised the Loss Mitigation Home Retention Options to reduce the claims against the MMI Fund and help more borrowers stay in their homes. These revisions included eliminating the maximum back-end debt-to-income ratio, the restriction on the principal, interest, taxes, and insurance that can be included in the claim, and the requirement that the existing mortgage be no more than 12 months passed due.<sup>42</sup>
- In 2013 FHA established updated PFSs and Deed in Lieu (DIL) requirements. These changes included using the Deficit Income Test (DIT) – a test to determine if expenses exceed income and whether a hardship exists – and eliminating the financial hardship/deficit income PFS requirement for service members who have received a Permanent Change of Station order.<sup>43</sup> In 2013, additional modifications were made to the FHA Loss Mitigation Home Retention Options. These changes included defining continuous income that can be considered in the transaction, allowing for arrearages to be included in partial claims, and allowing for modifications for mortgagors in bankruptcy.<sup>44</sup>
- In 2014, the updated PFS guideline required a minimum marketing period of 15 calendar days for all PFS transactions. It also clarified that non-arms-length transactions are permitted only if necessary to comply with state law.<sup>45</sup> Also, in 2014, FHA issued a mortgagee letter to increase the use of Claims Without Conveyance of Title (CWCOT) procedures. This letter also established that the Commissioner’s Adjusted Fair Market Value must be used for all foreclosure sales and PFS efforts.<sup>46</sup>
- In 2018, FHA issued a mortgagee letter implementing unique loss mitigation processes for Hurricanes Irma, Harvey, and Maria victims and the California Wildfires. These procedures were implemented to help homeowners stay home and reduce losses to FHA.<sup>47</sup> Later, in 2018, FHA issued a mortgagee letter in response to continued elevated default rates and lower utilization of loss mitigation options in Puerto Rico and the U.S. Virgin Islands. This mortgagee letter expanded loss mitigation assistance to borrowers in default.<sup>48</sup>

<sup>42</sup> Mortgagee Letter 2012-22, November 16, 2012: Revisions to FHA’s Loss Mitigation Home Retention Options.

<sup>43</sup> Mortgagee Letter 2013-23, July 9, 2013: Updated Pre-Foreclosure Sale (PFS) and Deed in Lieu (DIL) of Foreclosure Requirements.

<sup>44</sup> Mortgagee Letter 2013-32, September 20, 2013: Update to FHA’s Loss Mitigation Home Retention Options

<sup>45</sup> Mortgagee Letter 2014-15, July 10, 2014: Updated Requirements for Pre-Foreclosure Sales (PFS) and Deeds in Lieu (DIL) of Foreclosure.

<sup>46</sup> Mortgagee Letter 2014-24, November 26, 2014: Increasing Use of FHA’s Claims Without Conveyance of Title (CWCOT) Procedures

<sup>47</sup> Mortgagee Letter 2018-01, February 22, 2018: Loss Mitigation for borrowers with FHA-insured mortgages whose property and/or place of employment is located in Presidentially-Declared Major Disaster Areas, adversely affected by Hurricanes Harvey, Irma, Maria, certain California wildfires that occurred in October 2017 (FEMA-DR4344) or certain California Wildfires, Flooding, Mudflows, and Debris Flows that occurred in December 2017 (FEMA-DR-4353).

<sup>48</sup> Mortgagee Letter 2018-05, August 15, 2018: Updated Loss Mitigation for mortgagees servicing mortgage loans for borrowers with FHA-insured mortgages whose property and/or place of employment is located in the Presidentially-Declared Major Disaster Areas (PDMDAs) of Puerto Rico Hurricane Maria DR-4339 or Virgin Islands Hurricane Maria DR-4340 and Disaster Foreclosure Moratorium for certain FHA-insured mortgages secured by properties

- In 2019, HUD incorporated additional changes to streamline and revise Loss Mitigation Procedures for Presidentially Declared Major Disaster Areas (PDMDAs).<sup>49</sup>

## vii. COVID-19 and Changes in Loss Mitigation Options

The COVID-19 pandemic and policy response significantly impacted borrower behavior. Starting on March 18, 2020, a 60-day foreclosure moratorium was implemented for properties secured by FHA-insured mortgages, covering both the initiation of foreclosures and those already in progress.<sup>50</sup> Subsequently, this moratorium was extended several times, with the final extension on July 30, 2021, setting the end date as September 30, 2021.<sup>51</sup> During this period, the first legal action deadlines and reasonable diligence times were extended by 90 days from the moratorium's expiration. On February 7, 2022, it was further clarified that these deadlines would be extended 180 days from the end of the borrower's COVID-19 forbearance or the expiration of the foreclosure moratorium.<sup>52</sup>

Multiple FHA mortgagee letters issued during the pandemic period included provisions for loan forbearance, partial claims, loan modifications including 40-year term extensions, and incentive payments to servicers for completing COVID-19 Recovery options. On July 23, 2021, HUD set forth a range of COVID-19 Recovery Loss Mitigation Options, encompassing the COVID-19 Standalone Partial Claim, a zero-interest subordinate lien to cover arrearages, and the COVID-19 Recovery Modification, a 360-month loan modification.<sup>53</sup> On April 18, 2022, HUD introduced a 40-year loan modification as one of the COVID-19 recovery loss mitigation choices.<sup>54</sup> Effective April 30, 2023, the Federal Housing Administration (FHA) continued expanding its COVID-19 loss mitigation options by making it available to all eligible borrowers, regardless of the cause of their delinquency.<sup>55</sup>

Under Mortgagee Letter (“ML”) 2025-12, “Tightening and Expediting Implementation of the New Permanent Loss Mitigation Options”, effective October 1, 2025, COVID-19 Recovery Loss Mitigation Options are extended through and will expire on September 30, 2025. After that sunset date, eligible borrowers may avail themselves of loss mitigation options under a “loss mitigation waterfall” implemented sequentially via the following steps:

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located in areas of Puerto Rico and the U.S. Virgin Islands that the U.S. Department of Homeland Security’s Federal Emergency Management Agency (FEMA) has declared to be eligible for Individual Assistance (Affected Counties) as a result of Hurricane Maria (Puerto Rico Hurricane Maria DR-4339 and Virgin Islands Hurricane Maria DR-4340).

<sup>49</sup> Mortgagee Letter 2019-14, August 29, 2019: Updates to FHA’s Loss Mitigation Options for Borrowers in Presidentially-Declared Major Disaster Areas (PDMDAs)

<sup>50</sup> Mortgagee Letter 2020-04, March 18, 2020: Foreclosure and Eviction Moratorium in connection with the Presidentially Declared COVID-19 National Emergency.

<sup>51</sup> Mortgagee Letter 2021-03, January 21, 2021: Extension of Foreclosure and Eviction Moratorium in Connection with the Presidentially-Declared COVID-19 National Emergency.

<sup>52</sup> Mortgagee Letter 2022-02, February 7, 2022: Technical Update to the Extension of the Deadlines for the First Legal Action and Reasonable Diligence Time Frame.

<sup>53</sup> Mortgagee Letter 2021-18, July 29, 2021: COVID-19 Recovery Loss Mitigation Options.

<sup>54</sup> Mortgagee Letter 2022-07, April 18, 2022, Update to the COVID-19 Recovery Loss Mitigation Options.

<sup>55</sup> Mortgagee Letter 2023-03, April 30, 2023, Expansion of the COVID-19 Recovery Loss Mitigation Options.

Exhibit I-1: Loss Mitigation Waterfall

| Step | Criterion                                                                                                                  | Yes                                                                          | No                                                  |
|------|----------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------|-----------------------------------------------------|
| 1    | Is the Borrower no more than 120 Days in Default and able to repay arrearages over a set period of no more than 24 months? | Review for a <a href="#">Repayment Plan</a>                                  | Proceed to Step 2                                   |
| 2    | Does the Borrower require a period of reduced or suspended payments before they are able to resume payments?               | Review for a <a href="#">Forbearance</a>                                     | Proceed to Step 3                                   |
| 3    | Does the Borrower attest they can resume making their current Mortgage Payments?                                           | Review for a <a href="#">Standalone Partial Claim</a>                        | Proceed to Step 4                                   |
| 4    | Can Standalone Loan Modification achieve the target payment?                                                               | Review for a <a href="#">Standalone Loan Modification</a>                    | Proceed to Step 5                                   |
| 5    | Can a Combination Loan Modification and Partial Claim achieve the target payment?                                          | Review for a <a href="#">Combination Loan Modification and Partial Claim</a> | Proceed to Step 6                                   |
| 6    | Does the Borrower qualify for a Payment Supplement?                                                                        | Review for a <a href="#">Payment Supplement</a>                              | Return to Step 5, if required, or proceed to Step 7 |
| 7    | Does the Borrower meet the requirements to participate in a Home Disposition Option?                                       | Review for a <a href="#">PFS</a>                                             | Proceed to Step 8                                   |
| 8    | If an approved PFS marketing period is unsuccessful, review for a <a href="#">DIL of Foreclosure</a>                       | <a href="#">DIL of Foreclosure</a>                                           | Foreclosure                                         |

Borrowers must complete three successive timely monthly payments under a Trial Payment Plan (TPP) to remain eligible for any of the above waterfall loss mitigation options and are only permitted a single loss mitigation option per 24-month period.

ML 2025-21, “Updates to Mortgagee Letter 2025-12, *Tightening and Expediting Implementation of the New Permanent Loss Mitigation Options*” incorporates minor changes to facilitate implementation of servicing and loss mitigation announced in the above referenced ML 2025-12.<sup>56</sup>

#### viii. LIBOR to SOFR Transition

Mortgagee Letter 2023-09 requires indexation of adjustable-rate loans to the Secured Overnight Financing Rate (SOFR) in place of the London Interbank Offered Rate (LIBOR), which has been discontinued. This change affects the way interest rates are calculated for ARMs, affecting both

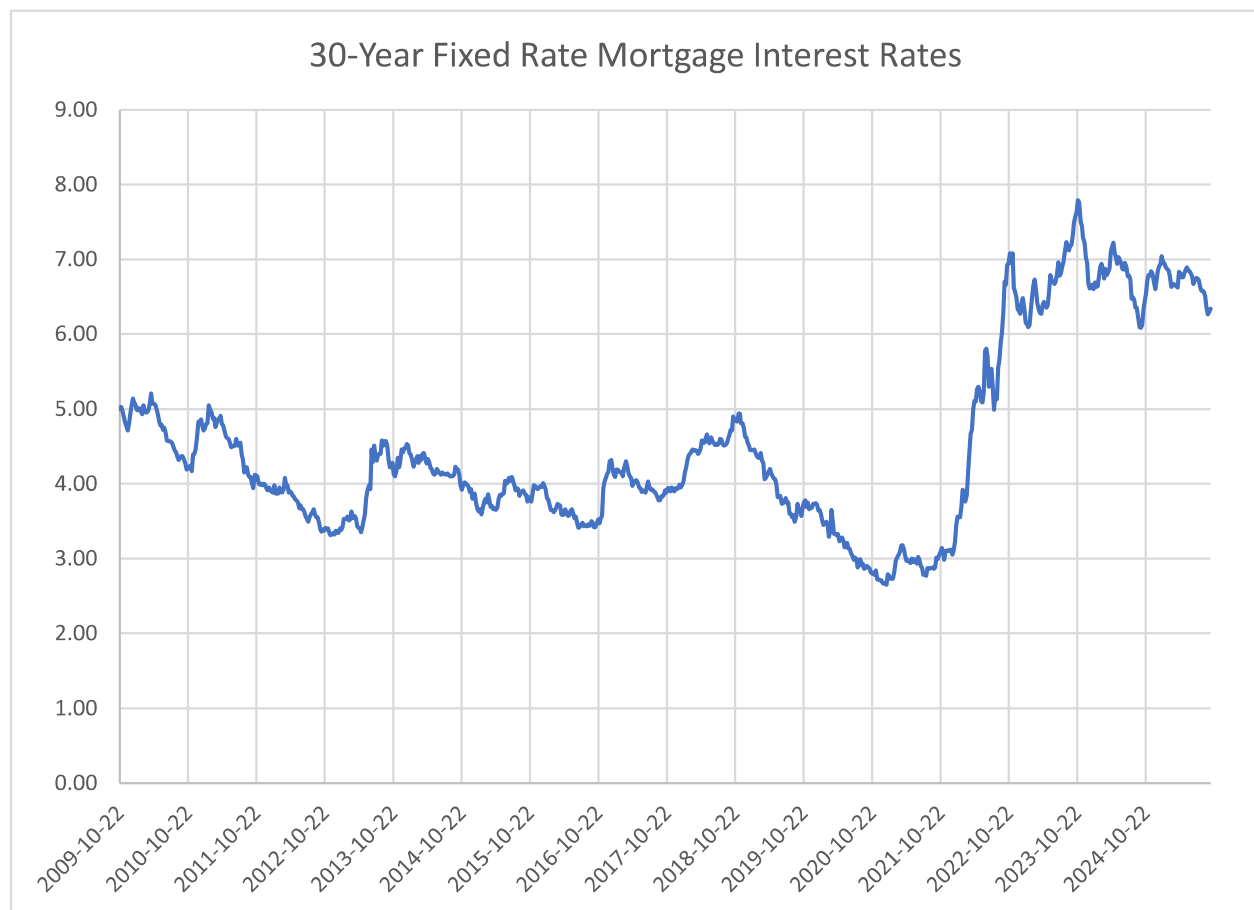
<sup>56</sup> Mortgagee Letter 2025-21, September 24, 2025: Updates to Mortgagee Letter 2025-12, *Tightening and Expediting Implementation of the New Permanent Loss Mitigation Options*.

new originations and existing mortgages. FHA has implemented provisions to ensure a smooth transition for existing and new adjustable-rate mortgages (ARMs) that were previously indexed to LIBOR.

#### D. Current and Future Market Environment Interest Rates

Average 30-year fixed rate mortgage interest rates, which fell to a low of 2.65% in January 2021, rose rapidly in 2022, peaking at 7.76% in November 2023 in the context of post-pandemic Federal Reserve tightening. Illustrated in Exhibit I-2, rates have generally exhibited a gradually declining trend since that time, remaining below 7% since early June 2024, dipping below 6.5% in early September 2025.

Exhibit I-2: Average 30-year Fixed Rate Mortgage Interest Rates<sup>57</sup>



#### i. Housing Market

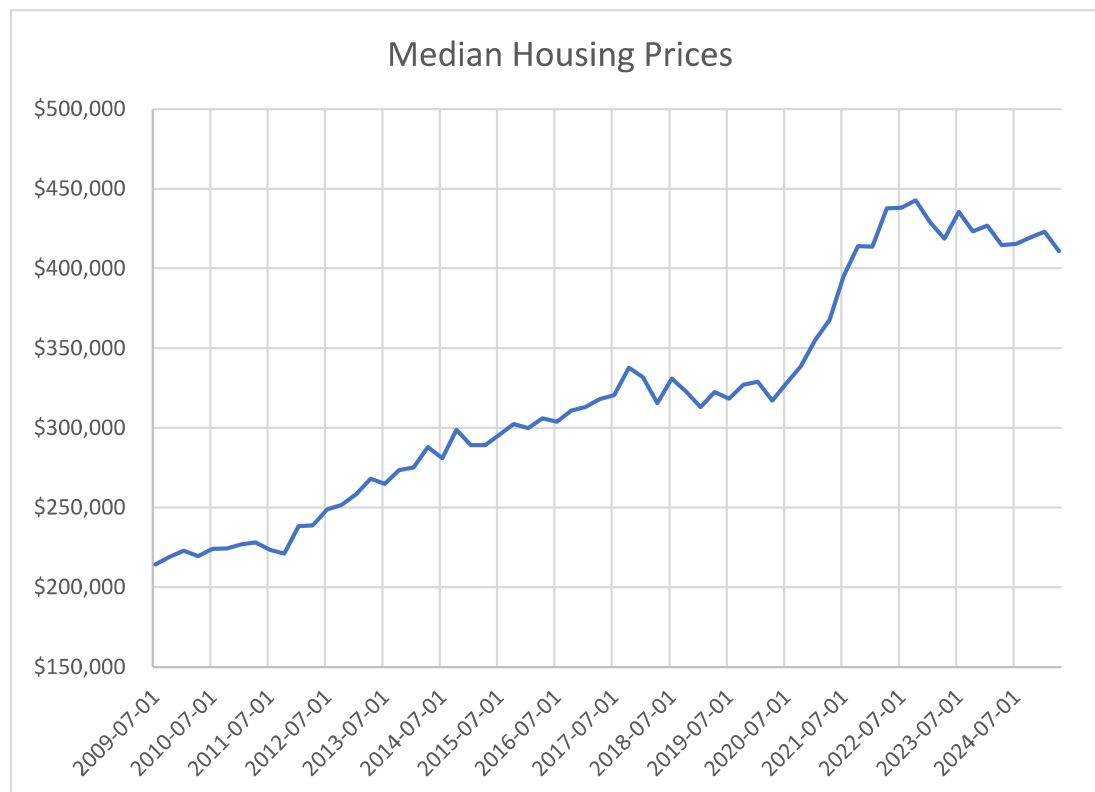
The number of homes for sale in August 2025 increased 21% over the prior year but remained 14% below the 2017-2019 pre-pandemic August average. The sales inventory is projected to reach

<sup>57</sup> Freddie Mac, 30-Year Fixed Rate Mortgage Average in the United States [MORTGAGE30US], retrieved from FRED, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/MORTGAGE30US>, October 4, 2025.

pre-pandemic levels nationally this fall is based on recent trends. Inventory levels have normalized in 39 of the 100 largest markets, with inventory surpluses relative to pre-pandemic levels in Denver, Colorado, Austin and San Antonio, Texas, Stockton and San Jose, California, Lakeland and Tampa, Florida, and New Orleans, Louisiana. New listings in May 2025 were 19% below 2017-2019 averages.

Housing price growth has slowed to the slowest rate in almost two years. Median sales prices, which peaked at \$442,600 in 2022Q4, had fallen to \$410,800 as of Q2 2025, as shown in Exhibit I-3. As of mid- 2025, 19 major US markets showed year-over-year home price declines, concentrated in southern and western regions of the country. Housing price declines have put some homeowners into a negative equity position. One estimate puts the share of FHA loans in a negative equity position at 2.6% concentrated among recent originations in Cape Coral, FL, North Port, FL, and Austin, TX.

Exhibit I-3: Median Sales Price of Houses Sold for the United States<sup>58</sup>



## ii. Mortgage Credit

Per the New York Federal Reserve Household Debt and Credit Report for Q2 2025, mortgage balances shown on consumer credit reports grew by \$131 billion during the second quarter of

<sup>58</sup> U.S. Census Bureau and U.S. Department of Housing and Urban Development, Median Sales Price of Houses Sold for the United States [MSPUS], retrieved from FRED, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/MSPUS>, October 4, 2025.

2025, totaling \$12.94 trillion at the end of June. Origination volume was \$458 billion in the second quarter. The median credit score of newly originated mortgage loans increased by 5 points. Transition into early delinquency was relatively stable, with transition into serious delinquency, defined as 90 days or more past due, increased slightly. Approximately 53,000 consumers had new foreclosure notations in credit reports, a decline from the prior quarter.

Based on their National Delinquency Survey, the Mortgage Bankers Association (MBA) reported that the national delinquency rate (including loans at least one payment past due, but excluding loans in the process of foreclosure) was 3.93 % as of June 30, 2025. This figure represents an 11 basis-point decrease from the prior quarter and is 4 basis points below the corresponding figure as of June 30, 2024.

In June 2025, FHA reported a serious delinquency rate, comprised of loans with at least three payments past due or in foreclosure or bankruptcy, of 4.30%, an increase over the 3.68% figure one year before.

## E. Structure of this Report

The remainder of this report is divided into the following sections:

Section II. Summary of Findings: Presents the economic net worth and insurance-in-force of the Forward portfolio as of the end of FY 2025.

Section III. Characteristics of the MMI SF Forward Books of Business: Presents various characteristics of the SF Forward portfolio for FYs 1996 through 2025.

Section IV. MMI Fund Performance under Alternative Scenarios and Sensitivity Testing: Presents the SF Forward portfolio economic net worth using alternative economic scenarios.

Section V. List of Methodology Appendices: Provides a summary of the models utilized in the analysis.

Section VI. Qualifications and Limitations: Describes the main assumptions and the limitations of the data and models relevant to the results presented in this Review.

Appendix A. Data Reconciliation: This section provides the data sources, processing and reconciliation tables used for this model.

Appendix B. Econometric Analysis of Mortgage Status Transitions and Terminations: Provides a technical description of our econometric models of default, claim, and prepayment for individual mortgage product types along with a description of the explanatory variables used in the models.

Appendix C. Estimation, Forecasting, and Actuarial Projections: Describes the loan status transition framework as it relates to the estimated probability models, how those models are

applied in forecasting, and the application of the forecasted probabilities to the actuarial calculations that summarize future loan performance.

Appendix D. Loss Severity and Cash Flow Analysis: Provides a technical description of the loss severity methodology and cash flow model.

Appendix E. Stochastic Simulation Models: Discusses the estimation and application of stochastic simulation models that are used to generate alternative forecasts for sensitivity analysis of our baseline estimates of economic net worth for the Single-Family portfolio.

Appendix F. Comparison of HUD and ITDC Models and Assessment of Vulnerabilities: As part of the statutory actuarial review process, the results of review of HUD's Forward and HECM models will be provided as an addendum to this report following its official publication. This addendum will include supplemental documentation and analysis that were not available at the time of release but are necessary to provide enhanced transparency and completeness of the actuarial review. The addendum will be published promptly upon finalization and will be considered an integral component of the actuarial review for the 2025 fiscal year.

Appendix G. Tables of Historical and Projected Termination Rates: Provides finger tables of conditional and cumulative claim and prepayment terminations by endorsement cohort years and policy years for each mortgage product. These are provided in spreadsheet files as a separate addendum to the report.

Appendix H. Logistic Model Estimation Results: Provides tables of estimated coefficients for each of the loan status transition probability models, including explanatory variables names and descriptions. These are provided in spreadsheet files as a separate addendum to the report.



## II. Summary of Findings

This section presents the projected economic net worth and insurance-in-force of the FY 2025 SF Forward MMI portfolios endorsed in FY 1995 or later. In addition to the capital resources as of the end of the fiscal year, the economic net worth of the SF Forward MMI portfolio depends on the discounted net present value of the future cash flows from the surviving portfolio of loans existing at the start of the valuation forecast (the end of the fiscal year under review). A fiscal year's economic net worth calculation does not include the effect of endorsements in future fiscal years. According to NAHA, the economic net worth of the Fund is defined as the "cash available to the Fund, plus the net present value of all future cash inflows and outflows expected to result from the outstanding mortgages in the Fund." We estimated the current economic net worth for the Forward portfolio as the sum of the amount of capital resources and the net present value of all expected future cash flows of the active Forward loans as of the end of FY 2025.

### A. The FY 2025 Actuarial Review

The 2025 Review estimates the economic net worth of the SF Forward portfolio as of the end of FY 2025 (September 30, 2025). The objectives of our analysis include:

- Analysis of historical loan performance using data provided by FHA, developing econometric models, estimating their parameters, and generating future performance based on economic forecasts in the PEA. The economic net worth of the Fund is determined by comparing estimates from the models with the Fund's capital resources.
- Evaluation of the historical experience of the Fund, including loan termination experience due to claims and prepayments and losses associated with claims.
- Projection of future loan termination rates and their corresponding cash flows of the existing Fund portfolio.
- Estimation of the present economic net worth and insurance-in-force of the Fund.

This Review is carried out by examining historical loan performance data supplied by FHA, creating econometric models with the estimation of their parameters, and generating economic scenarios consistent with the PEA. Econometric models are employed to forecast the Fund's future cash flows, and their present value is compared to the Fund's financial resources to determine the economic worth of the Fund.

Estimation of the loan status transition models utilized loan-level data on the Fund's historical loan performance from the mid-1990s through to the end of 2025. The performance of FHA loans through the 2007-2010 mortgage crises, the period of recovery and declining interest rates that followed the crisis, and the recent COVID-19 emergency have all provided real-world "stress tests" upon which to train our econometric models and develop forecasts of future performance. Further discussion and in-depth descriptions of the individual models, their underlying

assumptions, and comprehensive econometric outputs are provided in a series of appendices to the report.

## B. Economic Net Worth

The Economic Net Worth is calculated as the sum of available cash in the Fund and the Cash Flow NPV of all anticipated future cash inflows and outflows related to the mortgages currently insured by the MMI Fund. For the 2025 Review, we determined the Cash Flow NPV of the MMI Fund using data through September 30, 2025. This estimation involved an analysis of historical loan performance based on data from FHA, the creation of predictive models for loan transitions and losses, and the utilization of these model outcomes in conjunction with economic projections from OMB and Moody's to forecast the future cash flows of the MMI Fund. The NPV of these cash flows, combined with the MMI Fund's capital resources, constitutes the economic net worth of the MMI Fund.

Capital resources represent the Fund's net assets that can be converted into cash to fulfill the Fund's obligations, such as the payment of claims as they become due. These resources are determined by subtracting total liabilities from total assets and are documented in the year-end financial statements of the Fund.

Exhibit II-1 presents the components of the economic net worth for Fiscal Year 2025. The estimated Economic Net Worth is \$ 167.697 billion. The total economic net worth consists of the following components:

Exhibit II-1: Estimated Economic Net Worth of the Forward Portfolio in the MMI Fund at the End of FY 2025 (\$ Million)

| Item                                               | End of 2025  |
|----------------------------------------------------|--------------|
| Total Capital Resources*                           | \$ 130,533   |
| + NPV of Future Cash Flows on Outstanding Business | \$ 37,164    |
| Economic Net Worth                                 | \$ 167,697   |
| Insurance-In-Force (Unamortized)                   | \$ 1,795,689 |

\*Source: FHA Financial Statements for 2025

*Total Capital Resources* equals assets less liabilities on the Fund's balance sheet. The total capital resources are projected to be \$ 130.533 billion at the end of FY 2025. Data through September 2025 was used for the total capital resources.

*Net Present Value of Future Cash Flows on Outstanding Business* consists of discounted cash inflows and outflows. Forward cash inflows consist of premiums and recoveries. Cash outflows consist of claims, loss mitigation, and premium refund expenses. The cash flow model projects quarterly cash inflows and outflows using economic forecasts and loan performance projections. ITDC projects the Actuarial Central Estimate (ACE) of the MMI Forward Cash Flow NPV to be *positive* \$ 37.164 billion as of the end of FY 2025.

### C. Changes in the Economic Net Worth

As illustrated in Exhibit II-2, the projected Cash Flow NPV of the MMI Fund for FY 2025 decreased by \$ 852 million compared to the Fiscal Year 2024 estimate, shifting from positive \$38.016 billion to a positive \$ 37.164 billion. The capital resources available to the MMI Fund have grown, marking a 12.67 percent increase from a positive \$115.853 billion to a positive \$130.533 billion. The unamortized IIF increased 9.99 percent, from \$1,633 billion to \$ 1,796 billion. Exhibit II-2 compares our estimate of the MMI's Cash Flow NPV and IIF as of the end of Fiscal Year 2025 to the Cash Flow NPV estimate in the 2024 Review.

Exhibit II-2. Cash Flow NPV, Insurance-In-Force, and Capital Resources for FY 2025 (\$ Million)

| Item              | Cash Flow NPV | Capital Resources | Unamortized Insurance-In-Force |
|-------------------|---------------|-------------------|--------------------------------|
| 2024              | \$ 38,016     | \$ 115,853        | \$ 1,632,547                   |
| 2025              | \$ 37,164     | \$ 130,533        | \$ 1,795,689                   |
| Dollar Difference | \$ (852)      | \$ 14,681         | \$ 163,142                     |
| Percent Change    | -2.24%        | 12.67%            | 9.99%                          |

This change can be attributed to the changes in our models and the PEA baseline assumptions. To quantify the source of change in NPV, we identify key factors that affect the NPV and discuss total change using the following sources of change in Exhibit II-3.

Exhibit II-3. Decomposition of Changes in NPV from 2024 to 2025 (\$ Million)

| Decomposition Steps                                  | Change in NPV | NPV       |
|------------------------------------------------------|---------------|-----------|
| FY 2024 NPV in FY 2024 Actuarial Report              |               | \$ 38,016 |
| - Update Model – Termination Model                   | \$ 5,441      | \$ 43,457 |
| - Update Model – Loss Severity Models                | \$ (5,350)    | \$ 38,108 |
| - Update Model – Loss Mitigation Model               | \$ (923)      | \$ 37,185 |
| - Update Data – FY 2025 Data for Cohorts 1995 – 2024 | \$ (318)      | \$ 36,866 |
| - Update Data – New Originations in FY 2025          | \$ 297        | \$ 37,164 |
| FY 2025 Estimate of NPV                              |               | \$ 37,164 |

- In 2025, we revisited our termination model and decided to remove a series of period indicators that control the loan termination volatilities in different periods. We kept the indicator variable capturing the prolonged impact of loss mitigation policy changes in response to the COVID pandemics. All model variables were selected via comprehensive collinearity tests and a Least Absolute Shrinkage and Selection Operator (LASSO) process to improve model fit and efficiency. The updated termination model naturally incorporates the historical volatilities in termination rates, while also controlled for artificially depressed claim rates during the COVID foreclosure moratorium period. This change increased the NPV on 2024 data by \$5.441 billion.

- As more data was available for Third-Party Sale (TPS) loss claims, we directly predicted the likelihood of different loss disposition types and implemented the generalized least-squares regression on loss severity rates for each disposition type. All variables were selected via collinearity tests and a LASSO process to improve model fit and efficiency. The updated models are expected to reflect the recent trends in loss severity development. The NPV was reduced by \$5.35 billion due to the updates in loss severity models.
- We also refreshed our loss mitigation model. Rather than estimate the loss mitigation amount directly, we predicted the loss mitigation costs as a percentage of unpaid loan balance, linking the mitigation costs with the total risk exposure. Collinearity tests and LASSO process are also performed to select model variables. The updated loss mitigation model resulted in a decrease of \$923 million in NPV.
- We then updated the economic assumptions based on the FY 2026 Mid-Session Review of the President's Economic Assumptions (PEA). When incorporating the updated PEA assumptions along with amortization and loan terminations for cohorts 1995 through 2024, we observe a decrease in the NPV on the 2024 loan data by \$318 million.
- Finally, we measure the NPV impact due to the \$275 billion new endorsement volume during Fiscal Year 2025. Based on modeling projections, cohort 2025 is expected to have a net positive performance on the NPV, increasing the NPV by \$297 million.
- The overall change in the baseline NPV from the FY 2024 Review to this year's review is negative \$852 million, which is the sum of positive \$5.441 billion, negative \$5.35 billion, negative \$923 million, negative \$318 million, and positive \$297 million.

The Fund's present value of future cash flows is aggregated from separate estimates of the present value of future cash flows from each book of business and for each of the six mortgage product types. Exhibit II-4 shows the present values of future cash flows for each of the six mortgage product types from FY 1995 through FY 2025 books of business estimated to have survived to the end of FY 2025. From Exhibit II-4, the total present value of these future cash flows is a positive \$37.164 billion.

The housing and economic downturn of 2008 led to elevated claim rates for mortgages that originated during Fiscal Years 2005 to 2010. Due to the upfront MIP having already been collected and being part of the current capital resources, and considering their substantial origination volume, the Fiscal Year 2008 to 2012 cohorts are expected to incur more significant negative Cash Flow NPVs than other cohorts. Nevertheless, with the conclusion of the housing recession, property values hit a low point and subsequently began to rise. Consequently, mortgages originating in Fiscal Years 2013 through 2025 exhibit positive Cash Flow NPVs. This positive trend is further bolstered by the collection of MIPs over the mortgage's entire duration. Additionally, the historically low mortgage interest rates on loans originated in 2020, 2021, and

the initial quarter of 2022 reduced the refinance incentives, resulting in extended MIP collection periods in the simulation.

Also, a significant increase in new originations influenced the 2020 and 2021 Cash Flow NPV. There was a significant increase in refinance activity during this period. While this resulted in a decrease in Cash Flow NPV for older cohorts, it also increased Cash Flow NPV for the 2020 - 2022 cohorts as the older loans refinanced into newer cohorts.

Interest rates had remained historically low during the first half of Fiscal Year 2022, which tended to increase the NPV on loans originated during that time due to the reduced likelihood of refinancing. As interest rates started to rise in the latter part of Fiscal Year 2022, the refinance probability for these loans was expected to decline. With the resulting interest rate increase, the refinance rate remained relatively stable for mortgages originated in Fiscal Year 2022. The rising interest rates and subsequent mortgage rates throughout Fiscal Years 2022-2025 have reduced the projected level of prepayment rates for loans originating prior to 2023, due to the widely noted “lock-in” effect.

Exhibit II-4. Present Value of Future Cash Flows by Origination Fiscal Year & Mortgage Type as of the End of FY 2025 (\$ Million)

| Fiscal Year | FRM 30     | FRM 15   | ARM      | SR 30     | SR 15  | SR ARM   | Total      |
|-------------|------------|----------|----------|-----------|--------|----------|------------|
| 1996        | \$ 0.0     | \$ -     | \$ 0.0   | \$ (0.0)  | \$ -   | \$ (0.0) | \$ 0.0     |
| 1997        | \$ 0.1     | \$ -     | \$ 0.0   | \$ (0.0)  | \$ -   | \$ (0.0) | \$ 0.2     |
| 1998        | \$ 0.2     | \$ -     | \$ 0.1   | \$ (0.1)  | \$ -   | \$ (0.0) | \$ 0.2     |
| 1999        | \$ 1.0     | \$ -     | \$ 0.1   | \$ (0.2)  | \$ -   | \$ (0.0) | \$ 0.9     |
| 2000        | \$ 1.2     | \$ -     | \$ 0.3   | \$ (0.0)  | \$ -   | \$ (0.0) | \$ 1.4     |
| 2001        | \$ 0.0     | \$ -     | \$ -     | \$ (0.4)  | \$ -   | \$ (0.0) | \$ (0.4)   |
| 2002        | \$ (3.5)   | \$ -     | \$ (0.2) | \$ (0.3)  | \$ -   | \$ (0.4) | \$ (4.3)   |
| 2003        | \$ (2.6)   | \$ -     | \$ (0.1) | \$ (2.6)  | \$ -   | \$ (0.5) | \$ (5.8)   |
| 2004        | \$ (6.4)   | \$ -     | \$ (0.6) | \$ (1.7)  | \$ -   | \$ (1.2) | \$ (9.9)   |
| 2005        | \$ (15.8)  | \$ -     | \$ (1.3) | \$ (1.9)  | \$ -   | \$ (1.2) | \$ (20.3)  |
| 2006        | \$ (16.0)  | \$ -     | \$ (0.5) | \$ (0.8)  | \$ -   | \$ (0.1) | \$ (17.5)  |
| 2007        | \$ (21.4)  | \$ -     | \$ (0.2) | \$ (0.4)  | \$ -   | \$ (0.0) | \$ (22.1)  |
| 2008        | \$ (72.6)  | \$ -     | \$ (1.1) | \$ (3.8)  | \$ -   | \$ (0.5) | \$ (78.1)  |
| 2009        | \$ (121.6) | \$ -     | \$ (0.7) | \$ (19.8) | \$ -   | \$ (2.0) | \$ (144.1) |
| 2010        | \$ (116.3) | \$ -     | \$ (5.9) | \$ (10.9) | \$ -   | \$ (5.0) | \$ (138.1) |
| 2011        | \$ (80.8)  | \$ (0.0) | \$ (5.2) | \$ (7.1)  | \$ 0.0 | \$ (3.3) | \$ (96.4)  |
| 2012        | \$ (92.8)  | \$ 0.3   | \$ (1.9) | \$ (8.0)  | \$ 0.0 | \$ (0.3) | \$ (102.6) |
| 2013        | \$ 321.8   | \$ 0.8   | \$ 1.6   | \$ 66.0   | \$ 0.0 | \$ (0.0) | \$ 390.2   |
| 2014        | \$ 837.9   | \$ 0.3   | \$ 6.2   | \$ 43.7   | \$ 0.0 | \$ 0.1   | \$ 888.3   |
| 2015        | \$ 1,347.6 | \$ 0.7   | \$ 4.3   | \$ 175.6  | \$ 0.0 | \$ 0.1   | \$ 1,528.3 |
| 2016        | \$ 1,869.2 | \$ 1.8   | \$ 1.6   | \$ 127.3  | \$ 0.0 | \$ -     | \$ 1,999.9 |
| 2017        | \$ 2,309.0 | \$ 3.1   | \$ 1.7   | \$ 54.3   | \$ 0.1 | \$ -     | \$ 2,368.2 |

| Fiscal Year | FRM 30      | FRM 15   | ARM       | SR 30      | SR 15  | SR ARM    | Total       |
|-------------|-------------|----------|-----------|------------|--------|-----------|-------------|
| 2018        | \$ 1,942.8  | \$ 2.7   | \$ 1.3    | \$ 10.5    | \$ 0.0 | \$ -      | \$ 1,957.4  |
| 2019        | \$ 2,175.2  | \$ 2.8   | \$ 1.9    | \$ 22.4    | \$ 0.0 | \$ -      | \$ 2,202.4  |
| 2020        | \$ 5,631.1  | \$ 4.2   | \$ 0.2    | \$ 660.6   | \$ 0.0 | \$ -      | \$ 6,296.1  |
| 2021        | \$ 9,693.4  | \$ 10.7  | \$ 0.6    | \$ 1,866.1 | \$ 0.3 | \$ -      | \$ 11,571.1 |
| 2022        | \$ 7,124.1  | \$ 8.4   | \$ 1.9    | \$ 55.8    | \$ 0.1 | \$ -      | \$ 7,190.2  |
| 2023        | \$ 1,387.9  | \$ 0.9   | \$ (1.1)  | \$ 0.4     | \$ -   | \$ -      | \$ 1,388.1  |
| 2024        | \$ (278.6)  | \$ (0.9) | \$ (11.0) | \$ 13.4    | \$ -   | \$ -      | \$ (277.1)  |
| 2025        | \$ 247.3    | \$ (2.3) | \$ (12.9) | \$ 65.4    | \$ 0.0 | \$ -      | \$ 297.4    |
| Total       | \$ 34,061.2 | \$ 33.5  | \$ (20.8) | \$ 3,103.4 | \$ 0.6 | \$ (14.4) | \$ 37,163.6 |

#### D. Current Insurance-In-Force

Both the unamortized and the amortized IIF are presented in this Review. From 1996 to 2025, the total Unamortized IIF was \$ 1,796 billion, and the total Amortized IIF was \$ 1,582 billion. Unamortized IIF is the original mortgage amount of all active endorsements. The amortized IIF reflects the current outstanding loan balance of all active endorsements. Exhibit II-5 shows the total volume of new mortgage endorsements for each book of business, the unamortized IIF, and the amortized IIF as of the end of FY 2025.

Exhibit II-5. Endorsements and Insurance-in-Force as of the End of FY 2025 (\$ Million)<sup>59</sup>

| Fiscal Year | Mortgage Endorsement | Unamortized Insurance-in-Force | Amortized Insurance-in-Force |
|-------------|----------------------|--------------------------------|------------------------------|
| 1996        | \$ 64,448            | \$ 651                         | \$ 34                        |
| 1997        | \$ 67,012            | \$ 908                         | \$ 115                       |
| 1998        | \$ 93,274            | \$ 1,587                       | \$ 306                       |
| 1999        | \$ 111,837           | \$ 2,222                       | \$ 560                       |
| 2000        | \$ 84,866            | \$ 1,331                       | \$ 439                       |
| 2001        | \$ 121,639           | \$ 2,561                       | \$ 953                       |
| 2002        | \$ 131,416           | \$ 3,973                       | \$ 1,603                     |
| 2003        | \$ 115,971           | \$ 6,212                       | \$ 2,613                     |
| 2004        | \$ 107,621           | \$ 7,873                       | \$ 3,567                     |
| 2005        | \$ 57,975            | \$ 5,879                       | \$ 2,910                     |
| 2006        | \$ 51,733            | \$ 5,054                       | \$ 2,785                     |
| 2007        | \$ 56,516            | \$ 5,316                       | \$ 3,202                     |
| 2008        | \$ 171,806           | \$ 13,665                      | \$ 8,654                     |
| 2009        | \$ 330,385           | \$ 29,182                      | \$ 18,662                    |
| 2010        | \$ 297,502           | \$ 33,293                      | \$ 21,916                    |
| 2011        | \$ 217,642           | \$ 27,429                      | \$ 17,907                    |
| 2012        | \$ 213,272           | \$ 36,687                      | \$ 23,842                    |

<sup>59</sup> Source: SFDW.IDB\_1.

| Fiscal Year | Mortgage Endorsement | Unamortized Insurance-in-Force | Amortized Insurance-in-Force |
|-------------|----------------------|--------------------------------|------------------------------|
| 2013        | \$ 240,115           | \$ 54,396                      | \$ 36,960                    |
| 2014        | \$ 135,216           | \$ 19,250                      | \$ 14,144                    |
| 2015        | \$ 213,121           | \$ 37,836                      | \$ 28,914                    |
| 2016        | \$ 245,405           | \$ 57,286                      | \$ 45,145                    |
| 2017        | \$ 250,954           | \$ 66,313                      | \$ 53,993                    |
| 2018        | \$ 209,050           | \$ 54,131                      | \$ 46,109                    |
| 2019        | \$ 214,621           | \$ 57,614                      | \$ 50,700                    |
| 2020        | \$ 310,321           | \$ 136,031                     | \$ 120,217                   |
| 2021        | \$ 342,823           | \$ 253,621                     | \$ 227,595                   |
| 2022        | \$ 255,504           | \$ 222,515                     | \$ 207,287                   |
| 2023        | \$ 208,728           | \$ 178,545                     | \$ 172,775                   |
| 2024        | \$ 231,525           | \$ 202,532                     | \$ 198,993                   |
| 2025        | \$ 274,722           | \$ 271,797                     | \$ 270,045                   |
| Total       | \$ 5,427,020         | \$ 1,795,689                   | \$ 1,582,946                 |



### III. Characteristics of the MMI SF Forwards Books of Business

In this section, we examined the characteristics of the loan portfolio insured by the MMI Fund for 2025. Our analysis is divided into three key areas:

- Evaluation of loan volume and composition, considering different loan types.
- A comparison between new purchase loans and refinances.
- An examination of the distribution of loans based on various loan characteristics.

Furthermore, we conducted a comprehensive assessment of the FY 2025 cohort and compared it to prior cohorts to assess its potential impact on the future performance of the MMI Fund.

#### A. Volume and Share of Mortgage Originations

FHA endorsed \$ 274.722 billion in single-family forward mortgages in Fiscal Year 2025, bringing the MMI Fund's total unamortized IIF to \$ 1.796 trillion. Exhibit III-1 shows the FHA's count and volume of originations by fiscal year and mortgage product type.

As shown in the figure below, the count of new purchase loans followed a fluctuating trend, declining notably from Fiscal Year 2002 to Fiscal Year 2007, surging significantly through Fiscal Year 2010, and eventually stabilizing at levels akin to those in Fiscal Year 2000 - 2002. This oscillation resulted from the aggressive marketing strategies by Government Sponsored Enterprises (GSEs) and non-conforming lenders during the subprime era and their financial constraints when the housing market collapsed. Furthermore, the diminished capital strength of private mortgage insurance firms contributed to the increase in FHA's loan volume post-crash. With private mortgage insurance companies grappling with severe capital limitations, GSEs could not acquire or guarantee loans with less than a 20 percent down payment. Consequently, FHA assumed the primary role as the source of high Loan-to-Value (LTV) loans post-Fiscal Year 2008.

The trends in new purchase loan volumes exhibit a similar pattern. However, in the post-housing crisis, the volumes significantly surpassed those of the early 2000s. This surge was prompted by heightened loan size limits influenced by the GSEs, rendering more loans eligible for FHA insurance.

Exhibit III-1. Total Count and Volume of FHA-Insured Originations<sup>60</sup>

| Fiscal Year | Count of Originations |        |         |           |           |        | Volume of Originations (\$ Million) |        |        |           |           |        |
|-------------|-----------------------|--------|---------|-----------|-----------|--------|-------------------------------------|--------|--------|-----------|-----------|--------|
|             | FRM 30                | FRM 15 | ARM     | FRM 30 SR | FRM 15 SR | ARM SR | FRM 30                              | FRM 15 | ARM    | FRM 30 SR | FRM 15 SR | ARM SR |
| 1996        | 484,161               | 13,725 | 174,361 | 58,397    | 18,259    | 11,434 | 39,240                              | 812    | 17,155 | 5,048     | 1,028     | 1,146  |
| 1997        | 462,041               | 11,828 | 225,318 | 29,075    | 8,388     | 15,472 | 38,508                              | 744    | 22,817 | 2,760     | 481       | 1,693  |
| 1998        | 675,965               | 15,355 | 81,131  | 187,063   | 21,476    | 15,787 | 61,318                              | 1,054  | 8,526  | 19,200    | 1,402     | 1,761  |
| 1999        | 858,618               | 16,456 | 51,904  | 165,935   | 27,325    | 10,445 | 84,684                              | 1,228  | 6,343  | 16,618    | 1,766     | 1,180  |
| 2000        | 710,657               | 7,636  | 63,942  | 18,796    | 2,648     | 3,372  | 73,630                              | 579    | 8,046  | 2,065     | 163       | 374    |
| 2001        | 785,485               | 13,398 | 19,177  | 230,055   | 11,992    | 8,133  | 87,444                              | 1,200  | 2,655  | 28,278    | 984       | 1,076  |
| 2002        | 746,708               | 17,066 | 54,229  | 238,140   | 30,467    | 31,928 | 86,558                              | 1,622  | 7,914  | 28,781    | 2,308     | 4,232  |
| 2003        | 483,772               | 15,134 | 28,518  | 356,604   | 46,284    | 27,725 | 58,887                              | 1,552  | 4,409  | 43,645    | 3,618     | 3,857  |
| 2004        | 547,262               | 14,708 | 56,309  | 200,251   | 39,461    | 34,406 | 66,921                              | 1,474  | 8,715  | 23,129    | 2,796     | 4,583  |
| 2005        | 329,788               | 7,492  | 34,097  | 81,430    | 12,939    | 12,579 | 40,081                              | 730    | 5,255  | 9,375     | 815       | 1,715  |
| 2006        | 349,138               | 6,856  | 9,291   | 29,786    | 3,933     | 865    | 45,570                              | 702    | 1,476  | 3,602     | 249       | 128    |
| 2007        | 370,415               | 6,632  | 4,329   | 19,791    | 843       | 252    | 52,059                              | 692    | 754    | 2,895     | 63        | 42     |
| 2008        | 934,879               | 21,963 | 10,872  | 59,869    | 2,537     | 1,318  | 155,941                             | 2,760  | 2,434  | 10,147    | 242       | 260    |
| 2009        | 1,439,633             | 51,850 | 10,257  | 315,177   | 9,978     | 4,186  | 254,719                             | 7,206  | 2,613  | 63,624    | 1,235     | 947    |
| 2010        | 1,342,614             | 77,109 | 34,159  | 191,531   | 8,450     | 12,838 | 234,971                             | 10,807 | 8,408  | 39,151    | 1,080     | 3,046  |
| 2011        | 900,411               | 80,417 | 35,457  | 156,868   | 7,883     | 15,456 | 157,304                             | 12,270 | 9,119  | 33,652    | 1,356     | 3,912  |
| 2012        | 812,118               | 86,033 | 12,214  | 251,299   | 14,552    | 8,148  | 139,489                             | 13,601 | 3,179  | 52,326    | 2,516     | 2,138  |
| 2013        | 778,759               | 48,515 | 5,645   | 490,411   | 17,713    | 3,667  | 139,922                             | 7,399  | 1,665  | 87,856    | 2,306     | 938    |
| 2014        | 631,600               | 24,849 | 14,714  | 105,149   | 5,262     | 4,604  | 111,478                             | 3,392  | 4,006  | 14,887    | 498       | 922    |
| 2015        | 847,241               | 26,796 | 9,360   | 225,913   | 3,489     | 3,406  | 158,689                             | 3,552  | 2,769  | 46,744    | 397       | 966    |
| 2016        | 1,014,558             | 26,269 | 4,190   | 207,172   | 5,395     | 463    | 199,123                             | 3,295  | 1,351  | 40,894    | 604       | 138    |
| 2017        | 1,053,874             | 24,711 | 3,749   | 155,980   | 8,071     | 48     | 214,953                             | 3,197  | 1,010  | 30,879    | 903       | 12     |
| 2018        | 940,820               | 17,526 | 3,745   | 49,198    | 3,255     | 57     | 195,635                             | 2,357  | 1,000  | 9,741     | 302       | 14     |
| 2019        | 914,816               | 14,292 | 3,384   | 56,180    | 1,727     | 26     | 197,041                             | 1,930  | 934    | 14,554    | 155       | 7      |
| 2020        | 1,000,990             | 9,826  | 344     | 319,166   | 2,823     | 1      | 230,205                             | 1,359  | 113    | 78,227    | 417       | 0      |
| 2021        | 1,018,183             | 10,849 | 174     | 397,176   | 6,476     | 5      | 249,496                             | 1,462  | 64     | 90,955    | 845       | 1      |
| 2022        | 887,760               | 8,253  | 1,166   | 83,310    | 1,698     | 7      | 235,753                             | 1,143  | 383    | 18,012    | 211       | 2      |
| 2023        | 727,149               | 3,379  | 641     | 1,124     | 25        | -      | 207,592                             | 546    | 236    | 352       | 2         | -      |
| 2024        | 747,795               | 3,687  | 1,485   | 13,947    | 18        | -      | 225,276                             | 673    | 636    | 4,937     | 3         | -      |
| 2025        | 810,889               | 6,185  | 6,114   | 53,085    | 98        | 18     | 252,391                             | 1,140  | 2,384  | 18,777    | 22        | 8      |

Exhibit III-2 displays FHA's origination volume and market share in home purchase mortgages from calendar year 2000 through 2025Q1.

Exhibit III-2: FHA's Market Share in the Single-Family Forward Mortgage Market<sup>61</sup>

| Calendar Year | FHA Market Shares (Percent) |           |      | Origination Volume (\$ Billion) |        |           |        |     |        |
|---------------|-----------------------------|-----------|------|---------------------------------|--------|-----------|--------|-----|--------|
|               | Purchase                    | Refinance | All  | Purchase                        |        | Refinance |        | All |        |
|               |                             |           |      | FHA                             | Market | FHA       | Market | FHA | Market |
| 2000          | 9.90                        | 3.20      | 8.60 | 89                              | 897    | 7         | 220    | 96  | 1,117  |
| 2001          | 10.20                       | 5.80      | 8.20 | 97                              | 951    | 49        | 841    | 146 | 1,792  |

<sup>60</sup> Source: SFDW.IDB\_1.

<sup>61</sup> [https://www.hud.gov/sites/dfiles/Housing/images/FHA\\_SF\\_Market\\_Share\\_2025Q1.pdf](https://www.hud.gov/sites/dfiles/Housing/images/FHA_SF_Market_Share_2025Q1.pdf)

| Calendar Year | FHA Market Shares (Percent) |           |       | Origination Volume (\$ Billion) |        |           |        |     |        |
|---------------|-----------------------------|-----------|-------|---------------------------------|--------|-----------|--------|-----|--------|
|               | Purchase                    | Refinance | All   | Purchase                        |        | Refinance |        | All |        |
|               |                             |           |       | FHA                             | Market | FHA       | Market | FHA | Market |
| 2002          | 8.50                        | 3.20      | 5.40  | 90                              | 1,056  | 49        | 1,526  | 139 | 2,582  |
| 2003          | 6.40                        | 2.60      | 3.70  | 78                              | 1,221  | 77        | 2,970  | 155 | 4,191  |
| 2004          | 4.40                        | 2.00      | 3.20  | 58                              | 1,314  | 29        | 1,415  | 87  | 2,729  |
| 2005          | 2.60                        | 1.10      | 1.90  | 40                              | 1,512  | 16        | 1,514  | 56  | 3,026  |
| 2006          | 2.70                        | 1.30      | 2.00  | 38                              | 1,399  | 17        | 1,326  | 55  | 2,725  |
| 2007          | 3.90                        | 2.90      | 3.40  | 44                              | 1,140  | 33        | 1,166  | 77  | 2,306  |
| 2008          | 19.50                       | 12.90     | 16.10 | 143                             | 731    | 100       | 777    | 243 | 1,508  |
| 2009          | 28.10                       | 12.80     | 17.90 | 187                             | 664    | 171       | 1,331  | 358 | 1,995  |
| 2010          | 27.40                       | 8.60      | 14.90 | 165                             | 602    | 103       | 1,203  | 268 | 1,805  |
| 2011          | 25.32                       | 6.46      | 13.09 | 128                             | 505    | 60        | 931    | 188 | 1,436  |
| 2012          | 21.28                       | 7.38      | 11.38 | 125                             | 587    | 108       | 1,456  | 233 | 2,044  |
| 2013          | 15.94                       | 7.84      | 11.07 | 117                             | 734    | 87        | 1,111  | 204 | 1,845  |
| 2014          | 13.83                       | 5.62      | 10.56 | 105                             | 760    | 28        | 503    | 133 | 1,263  |
| 2015          | 16.74                       | 10.60     | 13.90 | 151                             | 903    | 82        | 776    | 233 | 1,679  |
| 2016          | 16.40                       | 8.10      | 12.36 | 173                             | 1,052  | 81        | 999    | 253 | 2,051  |
| 2017          | 14.94                       | 9.63      | 13.08 | 171                             | 1,143  | 59        | 616    | 230 | 1,760  |
| 2018          | 12.85                       | 9.09      | 11.80 | 155                             | 1,209  | 42        | 467    | 198 | 1,677  |
| 2019          | 13.65                       | 7.58      | 10.88 | 167                             | 1,225  | 78        | 1,028  | 245 | 2,254  |
| 2020          | 12.82                       | 4.35      | 7.41  | 190                             | 1,482  | 114       | 2,625  | 304 | 4,108  |
| 2021          | 10.85                       | 4.83      | 7.36  | 202                             | 1,863  | 124       | 2,574  | 326 | 4,436  |
| 2022          | 10.78                       | 7.55      | 9.82  | 174                             | 1,619  | 52        | 686    | 226 | 2,305  |
| 2023          | 14.22                       | 15.64     | 14.43 | 176                             | 1,239  | 34        | 219    | 210 | 1,458  |
| 2024          | 14.88                       | 10.59     | 13.70 | 192                             | 1,288  | 52        | 491    | 244 | 1,779  |
| 2025Q1        | 15.55                       | 11.81     | 14.46 | 42                              | 272    | 13        | 112    | 56  | 384    |

FHA's market share declined to a low of 1.1 percent in 2005. However, this trend reversed over the next several years, and by Fiscal Year 2009, FHA's market share had risen to 17.9 percent. Capital limitations encumbered private mortgage insurers and non-conforming lenders, effectively establishing FHA as the sole viable avenue for high Loan-to-Value (LTV) loans. Subsequently, the market share experienced a decline from 2018 through 2021 when it fell to 4.83 percent. It has since increased, to 10.78 percent as of 2022 and 14.22 percent in 2023, currently standing at 15.55 percent as of end of the first quarter of Calendar Year 2025.

## B. Originations by Location

FHA insures loans in all regions of the U.S., but about half of FHA's total dollar volume is concentrated in only ten states. Exhibit III-3 shows the percentage of FHA's total dollar volume originating in these ten states from FY 2020 through FY 2025. The states are ordered based on the dollar volume endorsed during FY 2025 to highlight the most recent changes.

Exhibit III-3. Percentage of Origination Volume by the Top 10 States<sup>62</sup>

| State | 2020  | 2021  | 2022  | 2023  | 2024  | 2025  |
|-------|-------|-------|-------|-------|-------|-------|
| TX    | 9.4%  | 9.6%  | 9.1%  | 10.9% | 11.6% | 11.4% |
| CA    | 14.4% | 12.4% | 11.3% | 10.5% | 10.7% | 10.8% |
| FL    | 8.9%  | 9.1%  | 9.1%  | 10.5% | 11.3% | 10.4% |
| GA    | 4.1%  | 4.2%  | 4.5%  | 5.1%  | 4.9%  | 4.8%  |
| AZ    | 3.4%  | 3.2%  | 3.1%  | 3.7%  | 3.9%  | 4.0%  |
| NC    | 2.3%  | 2.4%  | 2.6%  | 3.1%  | 3.4%  | 3.4%  |
| TN    | 2.2%  | 2.0%  | 2.2%  | 2.6%  | 2.8%  | 2.8%  |
| CO    | 3.5%  | 3.1%  | 2.8%  | 2.7%  | 2.7%  | 2.8%  |
| VA    | 3.0%  | 3.3%  | 3.1%  | 2.7%  | 2.6%  | 2.7%  |
| NJ    | 3.7%  | 4.0%  | 3.8%  | 3.0%  | 2.7%  | 2.7%  |

For the year 2025, the top three states of origination continue to be Texas, California, and Florida. Texas continues to have the largest state share of FHA volume at 11.4%. California has overtaken Florida for second largest share of FHA volume at 10.8%.

### C. Originations by Mortgage Type

Exhibit III-4 illustrates that the fully underwritten 30-year fixed-rate mortgage (FRM) has consistently constituted most of FHA's single-family business, averaging 78.8 percent over FYs 1995-2025. The proportion of total mortgages represented by 30-year FRMs began to evolve in the early 1990s when the FHA introduced insurance for adjustable-rate mortgages (ARMs) and streamline-refinancing mortgages (SRs). Over the following years, ARM and SR mortgages gradually claimed a more significant portion of annual loan originations, causing a decrease in the fully underwritten 30-year FRM share. FYs 1993, 1994, and 2003 marked the periods with the lowest shares of fully underwritten 30-year FRMs. This proportion has exceeded 90 percent each year starting FY 2018 through the present except for 2020-2021.

The ARM share of the portfolio, including SR ARMs, has declined substantially since reaching 9.9 percent in 2000, remaining less than 1 percent since 2016. Liquidity injected into the financial system in the context of the 2000-2001 recession and the 2008-2009 financial crisis, combined with declining inflationary expectations and a narrowing of spreads between mortgage interest rates and long-term Treasury yields, brought long-term primary mortgage to historic lows, incentivizing borrowers to shift from ARM to FRM products. FRM-30 mortgage rates have risen sharply since 2022 as noted earlier, but this increase has been accompanied by a simultaneous increase in ARM rates, explaining the continuation of market share trends from the prior low mortgage interest rate period.<sup>63</sup>

<sup>62</sup> Source: SFDW.IDB\_1.

<sup>63</sup> Justiniano, Alejandro ; Primiceri, Giorgio E. ; Tambalotti, Andrea, "The Mortgage Rate Conundrum", The Journal of Political Economy, 2022-01, Vol.130 (1), p.121-156

Meanwhile, 15-year FRMs grew from 1.2 percent in Fiscal Year 2007 to 6.4 percent in Fiscal Year 2012 but have generally declined since then, currently standing at 0.4 percent in Fiscal Year 2025. The 15-year SR continues to represent a negligible product type in the MMI Fund.

Exhibit III-4. Percentage of Origination Volume by Mortgage Type<sup>64</sup>

| Fiscal Year | Fully Underwritten Mortgages |              |       | Streamline Refinancing |             |          |
|-------------|------------------------------|--------------|-------|------------------------|-------------|----------|
|             | 30-Year FRMs                 | 15-Year FRMS | ARMs  | 30-Year SRs            | 15-Year SRs | ARMs SRs |
| 1996        | 60.9%                        | 1.3%         | 26.6% | 7.8%                   | 1.6%        | 1.8%     |
| 1997        | 57.5%                        | 1.1%         | 34.1% | 4.1%                   | 0.7%        | 2.5%     |
| 1998        | 65.7%                        | 1.1%         | 9.1%  | 20.6%                  | 1.5%        | 1.9%     |
| 1999        | 75.7%                        | 1.1%         | 5.7%  | 14.9%                  | 1.6%        | 1.1%     |
| 2000        | 86.8%                        | 0.7%         | 9.5%  | 2.4%                   | 0.2%        | 0.4%     |
| 2001        | 71.9%                        | 1.0%         | 2.2%  | 23.2%                  | 0.8%        | 0.9%     |
| 2002        | 65.9%                        | 1.2%         | 6.0%  | 21.9%                  | 1.8%        | 3.2%     |
| 2003        | 50.8%                        | 1.3%         | 3.8%  | 37.6%                  | 3.1%        | 3.3%     |
| 2004        | 62.2%                        | 1.4%         | 8.1%  | 21.5%                  | 2.6%        | 4.3%     |
| 2005        | 69.1%                        | 1.3%         | 9.1%  | 16.2%                  | 1.4%        | 3.0%     |
| 2006        | 88.1%                        | 1.4%         | 2.9%  | 7.0%                   | 0.5%        | 0.2%     |
| 2007        | 92.1%                        | 1.2%         | 1.3%  | 5.1%                   | 0.1%        | 0.1%     |
| 2008        | 90.8%                        | 1.6%         | 1.4%  | 5.9%                   | 0.1%        | 0.2%     |
| 2009        | 77.1%                        | 2.2%         | 0.8%  | 19.3%                  | 0.4%        | 0.3%     |
| 2010        | 79.0%                        | 3.6%         | 2.8%  | 13.2%                  | 0.4%        | 1.0%     |
| 2011        | 72.3%                        | 5.6%         | 4.2%  | 15.5%                  | 0.6%        | 1.8%     |
| 2012        | 65.4%                        | 6.4%         | 1.5%  | 24.5%                  | 1.2%        | 1.0%     |
| 2013        | 58.3%                        | 3.1%         | 0.7%  | 36.6%                  | 1.0%        | 0.4%     |
| 2014        | 82.5%                        | 2.5%         | 3.0%  | 11.0%                  | 0.4%        | 0.7%     |
| 2015        | 74.5%                        | 1.7%         | 1.3%  | 21.9%                  | 0.2%        | 0.5%     |
| 2016        | 81.1%                        | 1.3%         | 0.6%  | 16.7%                  | 0.2%        | 0.1%     |
| 2017        | 85.7%                        | 1.3%         | 0.4%  | 12.3%                  | 0.4%        | 0.0%     |
| 2018        | 93.6%                        | 1.1%         | 0.5%  | 4.7%                   | 0.1%        | 0.0%     |
| 2019        | 91.8%                        | 0.9%         | 0.4%  | 6.8%                   | 0.1%        | 0.0%     |
| 2020        | 74.2%                        | 0.4%         | 0.0%  | 25.2%                  | 0.1%        | 0.0%     |
| 2021        | 72.8%                        | 0.4%         | 0.0%  | 26.5%                  | 0.2%        | 0.0%     |
| 2022        | 92.3%                        | 0.4%         | 0.2%  | 7.0%                   | 0.1%        | 0.0%     |
| 2023        | 99.5%                        | 0.3%         | 0.1%  | 0.2%                   | 0.0%        | 0.0%     |
| 2024        | 97.3%                        | 0.3%         | 0.3%  | 2.1%                   | 0.0%        | 0.0%     |
| 2025        | 91.9%                        | 0.4%         | 0.9%  | 6.8%                   | 0.0%        | 0.0%     |
| Total       | 79.1%                        | 1.7%         | 2.5%  | 15.5%                  | 0.5%        | 0.6%     |

<sup>64</sup> Source: SFDW.IDB\_1.

## D. Initial Loan-to-Value Ratio Distributions

Based on studies of mortgage behavior, a borrower's equity position in the mortgaged house is one of the most critical drivers of default behavior. The larger the equity position a borrower has, the greater the incentive to avoid default. The original LTV is the complement of the borrower's equity at origination. Exhibit III-5 shows the distribution of mortgage originations by original LTV categories.

Exhibit III-5. Percentage of Origination Volume by Original LTV Category<sup>65</sup>

| Fiscal Year | Unknown LTV | <= 80 | > 80% <=90% | >90 <= 95 | > 95% <97% | >=97% |
|-------------|-------------|-------|-------------|-----------|------------|-------|
| 1996        | 8.6%        | 3.0%  | 10.7%       | 23.6%     | 31.2%      | 22.8% |
| 1997        | 5.6%        | 3.4%  | 11.4%       | 24.8%     | 32.5%      | 22.4% |
| 1998        | 16.3%       | 3.8%  | 12.0%       | 22.8%     | 27.5%      | 17.5% |
| 1999        | 10.1%       | 3.8%  | 9.8%        | 11.6%     | 26.0%      | 38.8% |
| 2000        | 4.1%        | 2.6%  | 6.8%        | 7.2%      | 31.2%      | 48.1% |
| 2001        | 17.6%       | 4.0%  | 9.9%        | 9.4%      | 22.4%      | 36.7% |
| 2002        | 11.4%       | 4.9%  | 11.2%       | 10.1%     | 23.8%      | 38.7% |
| 2003        | 9.2%        | 6.3%  | 12.8%       | 11.9%     | 23.4%      | 36.3% |
| 2004        | 12.9%       | 6.6%  | 11.7%       | 10.3%     | 22.5%      | 36.0% |
| 2005        | 15.1%       | 6.4%  | 10.7%       | 9.1%      | 22.2%      | 36.5% |
| 2006        | 15.2%       | 7.1%  | 10.7%       | 14.3%     | 19.9%      | 32.8% |
| 2007        | 14.3%       | 7.4%  | 11.7%       | 21.2%     | 18.2%      | 27.2% |
| 2008        | 21.9%       | 6.2%  | 12.2%       | 24.0%     | 14.1%      | 21.6% |
| 2009        | 9.7%        | 5.0%  | 13.3%       | 18.8%     | 35.7%      | 17.4% |
| 2010        | 0.1%        | 4.8%  | 14.5%       | 12.6%     | 58.8%      | 9.1%  |
| 2011        | 0.1%        | 4.9%  | 14.8%       | 14.1%     | 59.9%      | 6.3%  |
| 2012        | 0.0%        | 5.5%  | 13.4%       | 20.0%     | 57.2%      | 3.8%  |
| 2013        | 0.0%        | 5.7%  | 16.1%       | 27.2%     | 48.6%      | 2.3%  |
| 2014        | 0.0%        | 6.1%  | 14.1%       | 12.9%     | 65.0%      | 1.8%  |
| 2015        | 0.1%        | 6.1%  | 14.8%       | 12.9%     | 63.8%      | 2.2%  |
| 2016        | 0.0%        | 6.9%  | 16.1%       | 11.1%     | 64.1%      | 1.7%  |
| 2017        | 0.0%        | 7.9%  | 17.2%       | 10.1%     | 63.7%      | 1.2%  |
| 2018        | 0.0%        | 7.8%  | 16.8%       | 8.1%      | 66.2%      | 1.1%  |
| 2019        | 0.0%        | 7.6%  | 17.5%       | 7.8%      | 65.5%      | 1.7%  |
| 2020        | 0.1%        | 10.5% | 12.1%       | 12.3%     | 62.7%      | 2.4%  |
| 2021        | 0.0%        | 12.5% | 11.2%       | 14.5%     | 60.8%      | 0.9%  |
| 2022        | 0.0%        | 20.7% | 7.5%        | 10.8%     | 60.8%      | 0.2%  |
| 2023        | 0.0%        | 18.9% | 7.1%        | 9.7%      | 64.1%      | 0.2%  |
| 2024        | 0.0%        | 17.7% | 7.1%        | 9.7%      | 64.3%      | 1.0%  |
| 2025        | 0.0%        | 17.7% | 7.5%        | 9.3%      | 62.8%      | 2.7%  |

<sup>65</sup> Source: SFDQ.IDB\_1.

The distribution among original LTV categories had undergone significant shifts after FY 1998. During the period spanning from FY 2000 to FY 2006, over a third of loans insured had LTVs equal to or greater than 97 percent. However, this concentration in the highest-risk category gradually waned over the following years. In 2008, MMI imposed a 96.5 percent limit on the original LTV, with no additional allowances for financing closing costs. Loans with LTV greater than or equal to 97 percent have remained low for each FY since 2017. Since 2014, over 60 percent of mortgages have had LTV ratios falling between 95 percent and 97 percent.

In FY 2022, over 20 percent of mortgages had an initial LTV of 80 percent or lower, possibly related to refinance incentives in a historically low mortgage rate environment. Such loans have remained more than 17 percent of the total in each of the subsequent years.

The original LTV concentration of individual business books affects the predictive models in two ways. First, it serves as the starting position for updating the current LTV. Holding everything else constant, loans with higher original LTVs will experience a higher current LTV in future years. Second, the original LTV is also included in the models to capture potential behavioral differences among borrowers who self-select into different original LTV categories. For SR loans, we use the original LTV of the prior fully underwritten mortgage, updated for the local house price appreciation and amortization, as a proxy for this variable.

## E. Borrower Credit History Distributions

Since May 2004, all lenders originating loans for FHA insurance have been required to report borrower credit scores directly to HUD if any credit scores were ordered as part of the underwriting process. All loans going through the FHA TOTAL scorecard have credit scores obtained electronically by the affiliated automated underwriting systems. This provides a reliable source of credit score data. There are no exceptions to this requirement, so the credit scores collected through this channel are comprehensive and unbiased. These loans have become the primary source of credit score information. Credit scores pre-2004 were derived by UNICON or obtained from Fannie Mae as discussed below.

Exhibit III-6 shows the distributions of fully underwritten FHA mortgage loans by borrower credit score categories and origination years. The distribution among credit score categories remained stable for the FY 2005 through FY 2008 books. For loans originating after FY 2008, the credit score distribution significantly improved over the previous years. FY 2011 witnessed the highest percentage (62.5%) of originations with credit scores above 680. Loans with credit scores below 600 have remained less than 10 percent since 2009, currently standing at 5.7 percent.



Exhibit III-6. Percentage of Origination Volume by Credit Score among Fully Underwritten Loans<sup>66</sup>

| Fiscal Year | Missing | 300-499 | 500-599 | 600-639 | 640-679 | 680-719 | >720  |
|-------------|---------|---------|---------|---------|---------|---------|-------|
| 1996        | 97.4%   | 0.0%    | 0.8%    | 0.6%    | 0.5%    | 0.3%    | 0.4%  |
| 1997        | 97.3%   | 0.0%    | 0.8%    | 0.6%    | 0.5%    | 0.4%    | 0.4%  |
| 1998        | 97.2%   | 0.1%    | 0.9%    | 0.6%    | 0.5%    | 0.4%    | 0.4%  |
| 1999        | 96.8%   | 0.1%    | 1.0%    | 0.7%    | 0.6%    | 0.4%    | 0.4%  |
| 2000        | 82.1%   | 0.1%    | 4.4%    | 3.8%    | 3.7%    | 2.9%    | 3.0%  |
| 2001        | 76.9%   | 0.2%    | 5.4%    | 5.0%    | 4.8%    | 3.7%    | 4.1%  |
| 2002        | 68.7%   | 0.2%    | 7.5%    | 6.9%    | 6.5%    | 4.7%    | 5.5%  |
| 2003        | 63.9%   | 0.3%    | 8.8%    | 8.2%    | 7.6%    | 5.3%    | 6.0%  |
| 2004        | 44.4%   | 0.4%    | 14.0%   | 13.6%   | 12.0%   | 7.6%    | 8.1%  |
| 2005        | 6.5%    | 0.9%    | 26.1%   | 24.3%   | 20.0%   | 11.3%   | 10.9% |
| 2006        | 5.0%    | 0.9%    | 25.4%   | 24.5%   | 20.7%   | 11.5%   | 12.0% |
| 2007        | 4.4%    | 1.5%    | 31.2%   | 25.1%   | 18.9%   | 9.5%    | 9.3%  |
| 2008        | 2.5%    | 0.8%    | 21.0%   | 24.2%   | 22.7%   | 13.6%   | 15.1% |
| 2009        | 1.5%    | 0.0%    | 6.2%    | 18.0%   | 24.8%   | 20.6%   | 28.8% |
| 2010        | 1.6%    | 0.0%    | 1.0%    | 12.4%   | 25.0%   | 23.1%   | 36.9% |
| 2011        | 1.5%    | 0.0%    | 0.5%    | 8.4%    | 27.1%   | 24.0%   | 38.5% |
| 2012        | 1.1%    | 0.0%    | 0.6%    | 8.2%    | 30.7%   | 24.8%   | 34.6% |
| 2013        | 1.0%    | 0.0%    | 0.5%    | 6.5%    | 36.4%   | 27.7%   | 27.9% |
| 2014        | 0.7%    | 0.0%    | 1.0%    | 11.3%   | 41.5%   | 27.6%   | 17.8% |
| 2015        | 0.7%    | 0.0%    | 1.7%    | 14.5%   | 37.9%   | 27.4%   | 17.8% |
| 2016        | 0.7%    | 0.0%    | 1.9%    | 15.5%   | 36.4%   | 27.1%   | 18.4% |
| 2017        | 0.7%    | 0.0%    | 2.7%    | 17.7%   | 36.1%   | 25.7%   | 17.1% |
| 2018        | 0.6%    | 0.0%    | 4.3%    | 20.9%   | 36.9%   | 23.2%   | 14.1% |
| 2019        | 0.5%    | 0.0%    | 5.2%    | 22.5%   | 37.6%   | 21.6%   | 12.5% |
| 2020        | 0.6%    | 0.0%    | 3.4%    | 18.7%   | 39.1%   | 23.6%   | 14.5% |
| 2021        | 0.7%    | 0.0%    | 2.0%    | 18.6%   | 42.3%   | 23.1%   | 13.4% |
| 2022        | 0.6%    | 0.0%    | 4.5%    | 23.2%   | 40.5%   | 20.3%   | 10.8% |
| 2023        | 0.6%    | 0.0%    | 4.7%    | 19.5%   | 36.3%   | 23.3%   | 15.6% |
| 2024        | 0.7%    | 0.0%    | 4.8%    | 17.0%   | 31.2%   | 23.9%   | 22.4% |
| 2025        | 0.8%    | 0.0%    | 5.7%    | 17.1%   | 28.4%   | 23.1%   | 25.0% |

\* Excludes streamlined refinanced.

## F. Initial Relative Loan Size Distributions

The relative loan size variable is computed for each loan as loan origination amount divided by the average FHA loan size in the same location in the same year for the same product. Empirical results show that this variable is significant in prepayment-related terminations.

<sup>66</sup> Source: SFDW.IDB\_1.

FHA experience indicates that larger loans tend to perform better than smaller ones in the same geographical area, all else being equal. Larger loans incur claims at a lower probability; in those cases where a claim occurs, loss severity tends to be lower. Before the increase in FHA's loan limits in FY 2008, houses securing larger FHA loans tended to fall into the average house price range within their surrounding areas. Since this market is relatively liquid and there are a relatively large number of similar-quality homes in the area, the house price volatility of these houses tends to be relatively low compared to the house price volatility of shallow- and high-priced houses. With the increased FHA loan size limit, FHA started endorsing higher-priced houses after FY 2008.

Exhibit III-7 displays the percentage of new fully underwritten mortgage originations within each relative loan size category, controlling for credit subsidy cohort and property state. The distribution remained reasonably stable over time, with the most substantial share of the 100 percent and 125 percent of area loan size categories. Nevertheless, since Fiscal Year 2000, there has been a continuous increase in the variance among loan size categories. The proportion in the highest loan size category (above 150 percent of average loan size) had risen from 11.03% in Fiscal Year 2000 to 26.54% in Fiscal Year 2007 but decreased to 13.18% in 2020. As of 2025, the proportion in the highest loan size category is 14.22%.

The share in the lowest loan size category (less than or equal to 50% of average loan size) peaked at 12.34% in 2011, dropping to 9.72% in 2025.

Exhibit III-7. Percentage of Origination Count by Relative Loan Size <sup>67</sup>

| Cohort Year | <=50% Loan Size | 75% Loan Size | 100% of Loan Size | 125% of Loan Size | 150% of loan Size | >150% Loan Size |
|-------------|-----------------|---------------|-------------------|-------------------|-------------------|-----------------|
| 1996        | 5.91%           | 19.82%        | 27.90%            | 21.62%            | 14.03%            | 10.72%          |
| 1997        | 5.80%           | 19.91%        | 27.87%            | 20.95%            | 14.65%            | 10.82%          |
| 1998        | 5.34%           | 19.15%        | 28.93%            | 21.82%            | 15.00%            | 9.76%           |
| 1999        | 5.63%           | 20.26%        | 28.04%            | 21.94%            | 13.66%            | 10.47%          |
| 2000        | 6.36%           | 20.66%        | 26.13%            | 22.64%            | 13.17%            | 11.03%          |
| 2001        | 5.98%           | 20.37%        | 25.94%            | 24.78%            | 12.69%            | 10.23%          |
| 2002        | 6.26%           | 20.69%        | 25.80%            | 24.37%            | 12.38%            | 10.52%          |
| 2003        | 5.85%           | 20.13%        | 26.41%            | 24.98%            | 12.37%            | 10.26%          |
| 2004        | 6.40%           | 20.07%        | 24.68%            | 23.50%            | 13.73%            | 11.62%          |
| 2005        | 5.99%           | 18.24%        | 23.10%            | 23.11%            | 15.51%            | 14.05%          |
| 2006        | 4.11%           | 14.98%        | 20.77%            | 22.41%            | 16.79%            | 20.93%          |
| 2007        | 3.46%           | 13.49%        | 18.37%            | 21.08%            | 17.06%            | 26.54%          |
| 2008        | 7.59%           | 18.41%        | 23.68%            | 19.60%            | 12.47%            | 18.25%          |
| 2009        | 9.80%           | 20.57%        | 24.04%            | 17.25%            | 11.44%            | 16.90%          |
| 2010        | 11.51%          | 22.53%        | 23.33%            | 15.78%            | 10.50%            | 16.34%          |
| 2011        | 12.34%          | 22.00%        | 22.57%            | 15.10%            | 10.52%            | 17.47%          |
| 2012        | 12.23%          | 22.37%        | 23.15%            | 15.39%            | 10.34%            | 16.52%          |
| 2013        | 10.91%          | 22.94%        | 23.88%            | 15.74%            | 10.49%            | 16.04%          |
| 2014        | 10.92%          | 21.38%        | 23.74%            | 16.28%            | 10.11%            | 17.58%          |
| 2015        | 11.41%          | 21.48%        | 22.81%            | 16.43%            | 11.32%            | 16.53%          |
| 2016        | 11.36%          | 21.61%        | 23.54%            | 16.46%            | 12.22%            | 14.81%          |
| 2017        | 11.21%          | 20.83%        | 22.96%            | 17.41%            | 12.38%            | 15.22%          |
| 2018        | 11.18%          | 20.40%        | 22.87%            | 17.88%            | 12.38%            | 15.29%          |
| 2019        | 11.03%          | 20.86%        | 22.51%            | 18.72%            | 12.38%            | 14.50%          |
| 2020        | 9.03%           | 20.52%        | 24.19%            | 20.22%            | 12.87%            | 13.18%          |
| 2021        | 9.25%           | 20.95%        | 23.64%            | 19.48%            | 12.83%            | 13.84%          |
| 2022        | 9.94%           | 20.19%        | 20.74%            | 18.42%            | 13.71%            | 17.00%          |
| 2023        | 11.07%          | 19.45%        | 21.00%            | 18.99%            | 13.74%            | 15.74%          |
| 2024        | 10.54%          | 19.14%        | 22.68%            | 19.94%            | 13.10%            | 14.60%          |
| 2025        | 9.72%           | 19.63%        | 23.73%            | 20.05%            | 12.64%            | 14.22%          |

## G. Initial Contract Interest Rate

Exhibit III-8 presents the average mortgage contract rate by type since FY 1996. Before FY 2020, the average contract rates in FY 2013 had been the lowest in this entire period. Rates had risen since FY 2013 but declined substantially in FY 2020 and FY 2021 in the context of pandemic-era

<sup>67</sup> Source: SFDW.IDB\_1.

stimulus. Interest rates for 30-year SRs in FY 2021, averaging 2.88 percent, contributed significantly to a surge in refinance activity in FY 2020 and FY 2021.

Interest rates increased rapidly in FY 2022 in response to factors including anti-inflation action by the Federal Reserve Board of Governors, rising to approximately 7% as of mid-FY 2025.

In general, an FRM with a lower initial contract rate tends to prepay at a slower speed. As interest rates continue to rise or remain steady, the prepayment rates of the recent originations are likely to remain low. The longer duration of these loans is reflected in our econometric models, so that additional insurance premium income is forecasted, thereby increasing the economic net worth of recent books with historically low contract rates. We note that there will be some level of prepayments associated with employment change and residential mobility, regardless of the level of interest rates.<sup>68</sup> Our econometric models fall under the general descriptions of the logit models that include both baseline and systematic components that determine conditional transition rates, so that projected transition rates will never reach either 0 or 1.

Also, a mortgage with a contract rate lower than the market rate tends to experience a lower probability of default because the borrower is incentivized to keep the below-market rate mortgage longer, even when experiencing some negative equity. This tendency is captured in our econometric models through the inclusion of variables measuring the length of time the default option may be in-the-money and not exercised, which we refer to as “credit burnout.” The recent low-interest-rate books are projected to experience fewer default episodes and claim terminations as mortgage rates rise, contributing to improving the portfolio economic net worth.

Exhibit III-8. Average Contract Interest Rate by Loan Type (Percent)<sup>69</sup>

| Fiscal Year | 30-Year FRMS | 15-Year FRMS | ARMs  | 30-Year SRs | 15-Year SRs | ARM SRs |
|-------------|--------------|--------------|-------|-------------|-------------|---------|
| 1996        | 7.88%        | 7.58%        | 6.54% | 8.01%       | 7.71%       | 6.80%   |
| 1997        | 7.89%        | 7.67%        | 6.47% | 8.19%       | 7.95%       | 6.75%   |
| 1998        | 7.29%        | 7.10%        | 6.11% | 7.47%       | 7.10%       | 6.47%   |
| 1999        | 7.39%        | 7.07%        | 6.21% | 7.23%       | 6.98%       | 6.02%   |
| 2000        | 8.30%        | 8.07%        | 6.99% | 8.19%       | 7.90%       | 6.38%   |
| 2001        | 7.41%        | 6.97%        | 6.03% | 7.31%       | 6.74%       | 5.93%   |
| 2002        | 6.95%        | 6.45%        | 5.27% | 6.82%       | 6.30%       | 5.26%   |
| 2003        | 6.08%        | 5.51%        | 4.42% | 5.99%       | 5.48%       | 4.44%   |
| 2004        | 6.08%        | 5.52%        | 4.41% | 5.92%       | 5.46%       | 4.34%   |
| 2005        | 5.94%        | 5.64%        | 4.78% | 5.85%       | 5.65%       | 4.67%   |
| 2006        | 6.29%        | 6.14%        | 5.36% | 6.10%       | 6.02%       | 5.03%   |
| 2007        | 6.51%        | 6.40%        | 5.62% | 6.38%       | 6.22%       | 5.59%   |

<sup>68</sup> Non-streamlined refinance (NSR) prepayment propensity attributable to housing turnover would be captured primarily in the segment of “relative spread” variable measuring refinance incentive spline value less than zero (i.e. mortgage note rate less than market rate) and in seasonal indicator variables included in transition model specifications.

<sup>69</sup> Source: SFDW.IDB\_1.

| Fiscal Year | 30-Year FRMS | 15-Year FRMs | ARMs  | 30-Year SRs | 15-Year SRs | ARM SRs |
|-------------|--------------|--------------|-------|-------------|-------------|---------|
| 2008        | 6.33%        | 5.95%        | 5.39% | 6.09%       | 5.64%       | 5.33%   |
| 2009        | 5.62%        | 5.14%        | 5.05% | 5.26%       | 4.81%       | 4.54%   |
| 2010        | 5.14%        | 4.62%        | 3.98% | 5.13%       | 4.65%       | 4.28%   |
| 2011        | 4.65%        | 4.16%        | 3.51% | 4.63%       | 4.16%       | 3.69%   |
| 2012        | 3.98%        | 3.46%        | 3.14% | 3.98%       | 3.53%       | 3.38%   |
| 2013        | 3.62%        | 3.16%        | 2.82% | 3.71%       | 3.36%       | 2.86%   |
| 2014        | 4.30%        | 3.71%        | 3.31% | 4.51%       | 3.91%       | 3.39%   |
| 2015        | 4.03%        | 3.47%        | 3.26% | 3.99%       | 3.69%       | 3.36%   |
| 2016        | 3.91%        | 3.40%        | 3.23% | 3.87%       | 3.53%       | 3.35%   |
| 2017        | 4.03%        | 3.50%        | 3.18% | 3.75%       | 3.59%       | 3.02%   |
| 2018        | 4.54%        | 3.87%        | 3.51% | 4.08%       | 4.03%       | 3.49%   |
| 2019        | 4.68%        | 4.15%        | 4.00% | 4.23%       | 4.44%       | 4.02%   |
| 2020        | 3.63%        | 3.49%        | 3.47% | 3.50%       | 3.42%       | 3.50%   |
| 2021        | 3.04%        | 2.67%        | 2.65% | 2.88%       | 2.82%       | 2.33%   |
| 2022        | 4.06%        | 3.16%        | 3.11% | 3.08%       | 2.99%       | 2.52%   |
| 2023        | 6.18%        | 5.53%        | 4.93% | 5.74%       | 3.94%       | 0.00%   |
| 2024        | 6.57%        | 6.01%        | 5.37% | 6.42%       | 5.55%       | 0.00%   |
| 2025        | 6.19%        | 5.75%        | 5.17% | 6.24%       | 5.76%       | 5.36%   |

## IV. MMI Fund Performance under Alternative Scenarios

The Fund's Single-Family Forward economic net worth for FY 2025 depends on the economic conditions expected to prevail over the next 30 years and, most critically, during the next 10 years.

We have captured the most significant factors in the U.S. economy affecting the performance of the loans insured by the Fund using the following variables in our models:

- 30-year, 15-year, and adjustable-rate mortgage rates
- 1-year and 10-year constant maturity Treasury rates
- National and local house price indices
- National and local unemployment rates

The projected performance of FHA's current book of business, as measured by economic net worth, depends on future forecasts of these economic drivers. The baseline scenario for the primary economic drivers was developed consistently with the PEA. The PEA is published by the Office of Management and Budget in compliance with the requirements of the Federal Credit Reform Act.

### A. FHFA House Price Indices

The actuarial central estimates are based on the PEA for the quarterly future performance of the FHFA Purchase Only (PO) seasonally adjusted HPI for the period FY 2025 FQ3 to FY 2035 FQ4 and 3% annualized HPA for years after FY 2035.

FHFA publishes both purchase-only (PO) and all-transactions (AT) versions of their HPIs. Some prior reviews have expressed the view that the HPI PO version is necessarily more accurate than the HPI AT version due to the reliance of the latter on appraisal valuations in addition to observed sale prices. We use the national FHFA Purchase Only (PO) seasonally adjusted HPI and have applied the AT version of the FHFA HPIs in model estimation for deriving local and state HPI, due to the significantly broader regional coverage provided by the AT version of the HPI, including more than 300 additional Metropolitan Statistical Area (MSA) level HPIs.

Calhoun (1991) first noted the benefits of having appraisal based HPIs during periods when sales transactions are limited or in locations where they are non-existent. Calhoun (1991) also examined the potential for greater sample-selection bias when only sales transaction data are used. Simply stated, mortgage borrowers may be willing to refinance at appraised values well below their reservation prices for selling, so that relying solely on sales prices draws from the higher end of the house price distribution at any point in time. In our view, geographic aggregation bias far outweighs concerns about appraisal bias, particularly given the overall consistency between AT and PO versions of the HPI at the same level of geography. Later research by Calhoun, Harter-

Dreiman, VanderGoot (1998) and Leventis (2006) indicate that the actual evidence for systematic appraisal bias is mixed or inconclusive. On the other hand, geographic bias is large, immediate, and certain if the HPI PO version must be applied at the state level when no MSA-level HPI is available. Therefore, we opted for broader geographic coverage at the MSA level.

Nevertheless, we were required to use the PEA for the national FHFA PO HPI in developing our baseline forecast of portfolio economic net worth. To meet this requirement, we applied the following two-step procedure to obtain regional (MSA/State) HPI forecasts from the PEA national forecasts: (1) compute the period-by-period (FYFQ) differentials between the FHFA AT national forecast HPI appreciation rates and the corresponding appreciation rates for each regional HPI from the same FHFA AT forecast; and then (2) apply these differential appreciation rates to the PEA national PO HPI forecast to obtain regional HPIs forecasts consistent with the PEA national PO forecast. So as the PEA PO national forecast varies period-by-period, our regional HPIs (the newly created PEA MSA/State PO forecast) vary in a consistent manner, and enable us to retain the broader geographic coverage of the AT version of the FHFA HPIs (over 300 individual MSAs).

To be clear, we are not applying Moody's FHFA AT forecasts in place of the mandated PEA national HPI PO forecast. Changes in the local forecasts will still represent the pattern of house price appreciation for the PEA national forecast, plus regional differentials in appreciation rates based on observed historical patterns. Moody's AT and PO version national forecasts are quite consistent in terms of projected appreciation rates at both the national and regional levels, and Moody's baseline national forecasts are quite like the PEA. As described in Appendix E, alternative scenarios for sensitivity analysis based on our stochastic simulation models use a similar approach to go from the simulated national PO version HPI forecasts to the corresponding simulated regional forecasts. The same procedure for developing regional forecasts from PEA national HPI forecasts was applied for both Single Family Forward and HECM Fund performance.

## B. Interest Rates

Mortgage Letter (ML) 2023-9 required that the Secured Overnight Financing Rate (SOFR) replace LIBOR for both new and existing ARMs indexed to LIBOR in order to phase out LIBOR.

The Alternative Reference Rates Committee (ARRC) noted that regardless of what rate was chosen as a LIBOR alternative, there would need to be an adjustment for the difference between LIBOR and the fallback rate. Market participants preferred the 'historical mean/median approach,' which is based on the 5-year historical median difference between USD LIBOR and SOFR for the spread adjustment. Bloomberg published the following values shown in Exhibit IV-1 as the long-term spread adjustments, based on historical 5-year median spreads between USD LIBOR and compounded averages of SOFR:



Exhibit IV-1. Historical Median Difference between USD LIBOR and SOFR

| LIBOR tenor being replaced | Spread applied to SOFR based rate (bps) |
|----------------------------|-----------------------------------------|
| 1-week USD LIBOR           | 3.839                                   |
| 1-month USD LIBOR          | 11.448                                  |
| 2-month USD LIBOR          | 18.456                                  |
| 3-month USD LIBOR          | 26.161                                  |
| 6-month USD LIBOR          | 42.826                                  |
| 1-year USD LIBOR           | 71.513                                  |

The ARRC’s initial consultation demonstrated that a static spread could produce results that are as, or more, accurate than a potentially dynamic spread, and showed a static spread of 0.08% based on 5-Year median spread to SOFR for spread-adjusted loans with 5-years remaining maturity. In this review, we assume one-year SOFR plus a fixed 0.08% spread adjustment that measures the average difference between USD LIBOR and SOFR to be substantially equivalent to one-year LIBOR.

Alternative stochastic scenarios are simulated using the best GARCH models calibrated to the historical data.

### C. Unemployment Rates

Household unemployment directly impacts borrowers’ ability to make mortgage payments and is positively associated with mortgage default. However, due to the lack of household-level data, researchers have initially used aggregate unemployment rates as proxies for studying mortgage defaults, and only weak correlations were found (e.g., Deng, Quigley, and Order, 2000). More recent studies show that stronger relationships can be found when county or household level unemployment measures were adopted (e.g., Gyourko and Tracy, 2014; Gerardi, Herkenhoff, Ohanian, and Willen, 2018). Therefore, we include regional unemployment rates for model estimation and forecasting. However, for unemployment forecasting, the FY2026 Mid-Season Review of the PEA national unemployment rates were required by PWS to be used for the actuarial central estimate.

Similar to the process we used for regional HPI forecasts, regional unemployment rate forecasts incorporate a geographic dispersion factor calculated from Moody’s forecast of national and regional state- and MSA-level unemployment forecasts. The dispersions are then applied to the PEA national unemployment to obtain the forecasts for regional unemployment rates. The unemployment rate is countercyclical in nature. It tends to rise during economic downturns and fall during economic expansion periods. We simulate alternative unemployment scenarios based on a fitted GARCH model with the conditional mean replaced by baseline unemployment rates. A detailed discussion of historical unemployment rates and stochastic simulation can be found in Appendix E.

## D. Stochastic Scenarios

Our additional source of historical data for economic factors is Moody's Economy.com. Moody's has developed data from original sources, including the Federal Reserve, Bureau of Labor Statistics, Bureau of the Census, Bureau of Economic Analysis, Federal Housing Finance Agency, The Conference Board, Dow Jones, National Association of Realtors, and Freddie Mac. Depending on the data series, information is provided at the national, state, county, metropolitan area, and ZIP code level. Moody's data are combined with historical loan-level data from HUD's Single-Family Data Warehouse (SFDW) to build out loan-level panel data and event histories (defaults, cures, claims, prepayments) for use in estimating statistical models of loan performance. The estimated loan performance models are then combined with the forecasts of economic drivers based on the PEA to produce our baseline forecast.

In addition to the mandated baseline PEA forecasts, we apply four alternative stochastic scenarios based on Monte Carlo simulation of potential random deviations from the PEA baseline. Four scenarios for which we report estimates of economic net worth are:

- Optimistic Upside Scenario in Simulation, the path that is most favorable of the five selected paths to the SF Forward MMI Fund.
- Moderate Upside Scenario in Simulation, the path that is moderately favorable to the SF Forward MMI Fund.
- Moderate Downside Scenario in Simulation, the path that is moderately unfavorable to the SF Forward MMI Fund.
- Pessimistic Downside Scenario in Simulation, the path that is most unfavorable of the five selected paths to the SF Forward MMI Fund.

Each of the simulated scenarios is based on combinations of selected "percentile" paths for the economic drivers that correspond to favorable or unfavorable outcomes for the prospects of the Single Family Forward MMI Fund portfolio. Rising interest rates, rising housing values, and declining unemployment rates are favorable outcomes, because they lead to lower prepayments (increasing future premium income) and lower default, claim, and loss rates (reducing future losses). Conversely, declining interest rates, falling house prices, and rising unemployment rates are unfavorable outcomes, because they lead to higher prepayment rates (lowering future premium income) and higher default and claim rates (increasing future losses). Some elements of our more optimistic scenarios, such as higher interest rates, may not conform to the usual interpretation of favorable economic conditions, but are in fact favorable to the current economic net worth of the MMI Fund.

The combinations of selected percentile paths comprising each of the alternative scenarios described above are summarized here:

Scenario 1 – Optimistic Upside Scenario

Treasury and Mortgage Rates: 90<sup>th</sup> percentile

Unemployment Rate: 10<sup>th</sup> percentile

House Price Appreciation Rate: 90<sup>th</sup> percentile

#### Scenario 2 – Moderate Upside Scenario

Treasury and Mortgage Rates: 75<sup>th</sup> percentile

Unemployment Rate: 25<sup>th</sup> percentile

House Price Appreciation Rate: 75<sup>th</sup> percentile

#### Scenario 3 – Moderate Downside Scenario

Treasury and Mortgage Rates: 25<sup>th</sup> percentile

Unemployment Rate: 75<sup>th</sup> percentile

House Price Appreciation Rate: 25<sup>th</sup> percentile

#### Scenario 4 – Pessimistic Downside Scenario

Treasury and Mortgage Rates: 10<sup>th</sup> percentile

Unemployment Rate: 90<sup>th</sup> percentile

House Price Appreciation Rate: 10<sup>th</sup> percentile

The PEA forecast developed by the White House Council of Economic Advisors, Treasury, and OMB does not cover all the economy drivers that are included in our models. Additional economic variables that must be forecasted, such as FRM 15-Year and ARM origination rates, regional and local house price indices, and local unemployment rates, are developed using the PEA and additional forecast data from Moody's. Additional details may be found in the discussion of stochastic simulation models in Appendix E.

## E. NPV Values

The summary of the estimated Cash Flow NPV resulting from the Baseline PEA is \$ 37.164 billion. This projection constitutes the baseline against which the projections from the alternative scenarios are compared. Each scenario is shown in Exhibit IV-2. The range of projected results is between positive \$ 18.641 billion and positive \$ 47.200 billion.

Exhibit IV-2: Range of Cash Flow NPV Outcomes Based on Stochastic Simulations (\$ Million)

| Economic Scenario                             | Fiscal Year 2025 Cash Flow NPV |
|-----------------------------------------------|--------------------------------|
| Baseline PEA                                  | \$ 37,164                      |
| Alternative 1 - Optimistic Upside Scenario    | \$ 47,200                      |
| Alternative 2 - Moderate Upside Scenario      | \$ 42,712                      |
| Alternative 3 - Moderate Downside Scenario    | \$ 29,412                      |
| Alternative 4 - Pessimistic Downside Scenario | \$ 18,641                      |

Exhibit IV-3 presents a breakdown of the Cash Flow NPV by Cohort for the baseline PEA scenario along with the 4 simulated alternative scenarios.

Exhibit IV-3: Cash Flow NPV Summaries from Alternative Scenarios by Cohort (\$ Million)

| Cohort Year | Baseline PEA | Alternative - 1<br>Optimistic Upside | Alternative 2 -<br>Moderate Upside | Alternative 3 -<br>Moderate<br>Downside | Alternative 4 -<br>Pessimistic<br>Downside |
|-------------|--------------|--------------------------------------|------------------------------------|-----------------------------------------|--------------------------------------------|
| 1996        | \$ 0         | \$ 0                                 | \$ 0                               | \$ 0                                    | \$ 0                                       |
| 1997        | \$ 0         | \$ 0                                 | \$ 0                               | \$ 0                                    | \$ 0                                       |
| 1998        | \$ 0         | \$ 1                                 | \$ 1                               | \$ 1                                    | \$ 0                                       |
| 1999        | \$ 0         | \$ 0                                 | \$ 0                               | \$ 0                                    | \$ 0                                       |
| 2000        | \$ 3         | \$ 3                                 | \$ 3                               | \$ 3                                    | \$ 3                                       |
| 2001        | \$ (2)       | \$ (2)                               | \$ (2)                             | \$ (2)                                  | \$ (2)                                     |
| 2002        | \$ (4)       | \$ (5)                               | \$ (6)                             | \$ (6)                                  | \$ (6)                                     |
| 2003        | \$ (5)       | \$ (6)                               | \$ (6)                             | \$ (7)                                  | \$ (7)                                     |
| 2004        | \$ (10)      | \$ (12)                              | \$ (13)                            | \$ (14)                                 | \$ (14)                                    |
| 2005        | \$ (20)      | \$ (18)                              | \$ (19)                            | \$ (20)                                 | \$ (21)                                    |
| 2006        | \$ (17)      | \$ (18)                              | \$ (19)                            | \$ (20)                                 | \$ (21)                                    |
| 2007        | \$ (22)      | \$ (21)                              | \$ (22)                            | \$ (24)                                 | \$ (25)                                    |
| 2008        | \$ (78)      | \$ (66)                              | \$ (70)                            | \$ (79)                                 | \$ (82)                                    |
| 2009        | \$ (144)     | \$ (125)                             | \$ (132)                           | \$ (147)                                | \$ (154)                                   |
| 2010        | \$ (138)     | \$ (117)                             | \$ (126)                           | \$ (141)                                | \$ (150)                                   |
| 2011        | \$ (96)      | \$ (83)                              | \$ (89)                            | \$ (98)                                 | \$ (105)                                   |
| 2012        | \$ (103)     | \$ (90)                              | \$ (95)                            | \$ (105)                                | \$ (112)                                   |
| 2013        | \$ 390       | \$ 407                               | \$ 400                             | \$ 385                                  | \$ 381                                     |
| 2014        | \$ 888       | \$ 901                               | \$ 895                             | \$ 880                                  | \$ 884                                     |
| 2015        | \$ 1,528     | \$ 1,561                             | \$ 1,546                           | \$ 1,510                                | \$ 1,511                                   |
| 2016        | \$ 2,000     | \$ 2,059                             | \$ 2,032                           | \$ 1,969                                | \$ 1,959                                   |
| 2017        | \$ 2,368     | \$ 2,450                             | \$ 2,412                           | \$ 2,322                                | \$ 2,298                                   |
| 2018        | \$ 1,957     | \$ 2,067                             | \$ 2,018                           | \$ 1,892                                | \$ 1,844                                   |
| 2019        | \$ 2,202     | \$ 2,349                             | \$ 2,283                           | \$ 2,105                                | \$ 2,029                                   |
| 2020        | \$ 6,296     | \$ 6,585                             | \$ 6,445                           | \$ 6,121                                | \$ 5,998                                   |
| 2021        | \$ 11,571    | \$ 12,276                            | \$ 11,931                          | \$ 11,157                               | \$ 10,770                                  |
| 2022        | \$ 7,190     | \$ 8,532                             | \$ 7,917                           | \$ 6,226                                | \$ 4,923                                   |
| 2023        | \$ 1,388     | \$ 3,244                             | \$ 2,417                           | \$ (76)                                 | \$ (2,108)                                 |
| 2024        | \$ (277)     | \$ 2,096                             | \$ 1,045                           | \$ (2,172)                              | \$ (5,092)                                 |
| 2025        | \$ 297       | \$ 3,233                             | \$ 1,967                           | \$ (2,246)                              | \$ (6,063)                                 |
| Total       | \$ 37,164    | \$ 47,200                            | \$ 42,712                          | \$ 29,412                               | \$ 18,641                                  |

The 2025 Cash Flow NPV estimate provided by FHA is positive \$ 42.872 billion. Based on ITDC's Cash Flow NPV estimate utilizing the Baseline PEA and range of results from the stochastic simulation scenarios, we conclude that the FHA estimate of Cash Flow NPV is reasonable.

## F. Sensitivity Tests for Economic Variables and Important Assumptions

The stochastic scenario test results revealed important economic assumptions, such as interest rates, driving the NPV. Exhibit IV-4 illustrates NPV changes from baseline to 10 percent increases and decreases in home price appreciation, interest rates (including Treasury and mortgage interest

rates), loss severity, loss mitigation rates, and unemployment rates. For example, if a given HPA is 5% for a specific period, the HPA 10% up scenario would have 5.50% and the HPA 10% down scenario would be 4.50% for the same period; the same process applies to other variables.

Exhibit IV-4: NPV Sensitivity to Home Price Appreciation, Interest Rates, and Loss Severity

| Description              | NPV (% Change from the Baseline NPV)* |                |
|--------------------------|---------------------------------------|----------------|
|                          | Down 10%                              | Up 10%         |
| Interest Rates           | 34,067 (-8.3%)                        | 39,945 (7.5%)  |
| Loss Severity Rates      | 39,395 (6%)                           | 34,932 (-6%)   |
| Loss Mitigation Rates    | 38,395 (3.3%)                         | 35,932 (-3.3%) |
| House Price Appreciation | 36,940 (-0.6%)                        | 37,383 (0.6%)  |
| Unemployment             | 37,236 (0.2%)                         | 37,087 (-0.2%) |

The direction and magnitude of NPV impacts of shocks to these key model inputs are broadly consistent with economic intuition. Rising mortgage interest rates to reduce refinance incentives relative to baseline contribute to a slowdown in prepayment speeds, extending the period over which MIP can be collected. Because Treasury rates are incorporated into transition models as a measure of curve slope, simultaneous increases in 10-year and 1-year rates will not be significantly impactful on model-predicted transition outcomes.

Loss severity rates impact the NPV as these rates feed directly into realized loss from a claim. As loss severity rates increase, we anticipate a reduction in the NPV through a reduction in the amount recovered. Conversely, as loss severity rates decrease, we anticipate an increase in the recovery amount, resulting in an increase in cash flow NPV.

Exhibit IV-4 shows that all else being equal, 10% increase in loss mitigation rates results in a 3.3% decrease in NPV and vice versa. Loss mitigation rates are the third most sensitive of the tested five factors. Note that the purpose of the sensitivity test is to help investigate how sensitive the NPV is to the change of the estimated loss mitigation rates, all else being equal, rather than study whether loss mitigation improves or impairs the MMI fund. Loss mitigation options help keep borrowers from losing their homes, which is expected to slow future claim speeds. Whether the benefits of delaying or avoiding a claim outweigh the underlying cost of loss mitigation tools is not addressed in sensitivity tests.

Faster home price appreciation contributes to rising property values and falling LTV ratios, reducing borrower propensity to default, and reducing claim rates. At the same time, higher LTV may facilitate refinancing behavior, resulting in the reduction of MIP, mitigating the NPV benefits associated with lower claim rates. Conversely, the dominant effect of lower HPA is reduction in claim rates, mitigated by a slowdown in prepayment speeds.

Of the economic drivers for NPV, the model is least sensitive to changes to unemployment rate. We anticipate that a higher unemployment rate would increase mortgage delinquencies and

defaults, as job losses reduce borrowers' income, particularly affecting borrowers who often have less financial flexibility. As such, when the unemployment rate increases, the NPV decreases and when the unemployment rate decreases, the NPV increases.

## **V. List of Methodological Appendices**

This section describes the analytical approach implemented in this review. Detailed descriptions of the component models are provided in Appendices A through H. The following briefly summarizes how we process the data and develop component models in appendices.

### **Data Reconciliation (Appendix A)**

This appendix provides the data sources, processing and reconciliation tables used for this model. Loan-level panel data are extracted from HUD databases, supplemented by UNICON and Fannie Mae credit score data. A variety of derived variables are incorporated, for example estimates of current loan-to-value ratio utilizing original property value, amortization, and estimated regional home price appreciation. Macroeconomic time series data are merged into the estimation data to ensure the corresponding risk factors are appropriately integrated.

### **Econometric Analysis of Mortgage Status Transitions and Terminations (Appendix B)**

This appendix provides a technical description of our econometric models of quarterly default, claim, and prepayment for individual mortgage product types. We also provide a description of the explanatory variables used in the models.

A competing risk logistic regression or logit model approach is used to estimate the probability of loan transition events. We test the significance of parameters to achieve a parsimonious model that provides goodness-of-fit.

The multinomial logit approach has several benefits. First, logit models eliminate the likelihood of a negative probability for any estimated event. Second, the multinomial approach ensures the event probabilities sum to 100 percent. Third, it captures the zero-sum nature of the different termination events, whereby the increased probability of one risk decreases the probabilities of the other risks.

The transition models adopt four main categories of explanatory variables:

- Fixed initial loan characteristics, e.g. credit score, original loan size, loan size, loan purpose, spread relative to market mortgage rates at origination, and debt-to-income ratio;
- Dynamic variables based entirely on loan history, e.g. mortgage age, burnout, and default duration;



- Dynamic variables incorporating macroeconomic data separately or in conjunction with loan characteristics such as fixed-rate refinance incentive, local/national home price appreciation, current loan-to-value ratio, unemployment, and Treasury curve slope.
- Indicator variables capture the impacts of loss mitigation policy responses to COVID pandemics.

Transition models are estimated for each of the following six products: FRM-30 non-streamlined-refinance (NSR); FRM-15 NSR; ARM NSR; FRM-30 streamlined refinance (SR); FRM-15 SR; and ARM SR. For loans that are “current” as of the beginning of a quarterly period (i.e. less than 90 days delinquent), binomial logistic models are estimated for transitions to default, SR, and NSR. For “defaulted” loans that are 90 days or more delinquent, binomial models are estimated for cure, NSR, and claim.

A separate binomial logit transition model is estimated for each combination of product and transition event. For forecasting purposes, these logit regression models are reconfigured as multinomial logit competing hazard models following the approach suggested in Begg and Gray (1984).

### Single-family Forward Loan Performance Projections (Appendix C)

This appendix describes the loan status transition framework as it relates to the estimated probability models, how those models are applied in forecasting, and the application of the forecasted probabilities to the actuarial calculations that summarize future loan performance. 30-year projections are developed utilizing regression models and coefficients described in Appendix A together with macroeconomic risk factor values for housing prices, long-term mortgage rates, unemployment, and Treasury interest rates from the PEA forecast, supplemented by data from Moody’s DataBuffet.

### Loss Severity Model and Cash Flow Analysis (Appendix D)

This appendix provides a technical description of our econometric model of FHA mortgage loss severity rates.

### Stochastic Simulation Models (Appendix E)

This appendix discusses the estimation and application of stochastic simulation models used to generate alternative forecasts for sensitivity analysis of our baseline estimates of economic net worth for the Single-Family portfolio.

### Comparison of HUD and ITDC Models and Assessment of Vulnerabilities (Appendix F)



As part of the statutory actuarial review process, the results of review of HUD's Forward and HECM models will be provided as an addendum to this report following its official publication. This addendum will include supplemental documentation and analysis that were not available at the time of release but are necessary to provide enhanced transparency and completeness of the actuarial review. The addendum will be published promptly upon finalization and will be considered an integral component of the actuarial review for the 2025 fiscal year.

### Tables of Historical and Projected Termination Rates (Appendix G)

These tables, generated as output from processes set forth in Appendix C, are provided in a separate addendum to the main report.

### Logistic Model Estimation Results (Appendix H)

This appendix provides tables for the 48 estimated econometric models, including variable descriptions, explanatory variable functional forms (dummy, linear, spline, etc.), piece-wise linear spline knot specifications, estimated coefficients, and t-statistics for each status transition model for each of the six mortgage product types. Sample counts, likelihood values, and model chi-square statistics are also presented. These tables are provided as a separate addendum to the main report.

## VI. Qualifications and Limitations

The actuarial models used in this review are based on a theoretical framework and certain assumptions. This framework relates the default, claim, loss, and prepayment rates to several individual loan characteristics and certain critical macroeconomic variables. The models are estimated utilizing econometric regression techniques based on data from actual historical experience regarding the performance of FHA-insured mortgage loans. The parameters of the econometric models are estimated across a wide variety of loans originating starting fiscal 1996 and their performance under the range of economic conditions and mortgage market environments experienced during the past 30 years or less. The estimated models are used together with assumptions about future loan performance and certain key economic assumptions to produce future projections of the performance of the Fund.

The financial estimates presented in this Review require projections of events up to 40 years into the future.<sup>70</sup> These projections depend on the validity and robustness of the underlying models and the assumptions about future economic environments and loan characteristics. These include projections of future outcomes for key economic inputs to the models based on economic forecasts provided as components of the PEA. If the realized experience deviates from these or other assumptions, the actual results may differ, perhaps significantly, from current projections.

### A. Fundamental Data Limitations

The quality of any model built on historical data is constrained by the scope, availability, and accuracy of the data. Key variables determining market behavior may not be observed or they may be observed with error. Moreover, the theoretical specification of a model may not adequately capture the economic phenomena when there were material changes in market structure, regulatory policy, or technological advancement.

The econometric analysis in this Review uses data extracted from FHA's Single-Family Data Warehouse (SFDW). The volume and composition of the existing portfolio are based on FHA data as of September 30, 2025. While we have reviewed the integrity and consistency of these data and believe them to be reasonable, we have not audited them for accuracy. The information in this Review may not correspond exactly with other published analyses that rely on FHA data compiled at different dates or obtained from other data sources.

The data tables extracted from the SFDW for model estimation and forecasting included the following:

idb\_1 - Integrated Database (IDB) idb\_1 is a composite of 5 Single Family Forward legacy systems providing case-level data. idb\_1 contains informational data for 255 of the most frequently used

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<sup>70</sup> As such, the review does not consider cashflows past 2054 on extended term ("ET") modifications where the term to maturity is extended to 40 years.

attributes. The data is refreshed monthly with the most current month's data. IDB is not a historical datamart and cannot provide a case-level month-to-month audit trail.

idb\_2 - Single Family Forward legacy systems providing case-level data. idb\_2 contains informational data for approximately 250 of the less frequently used attributes. The data is refreshed monthly with the most current month's data.

decision\_fico\_score - The structure contains the Loan Underwriting Decision FICO Score that represents a composite of FICO scores generated from loan-applicant credit reports. It is refreshed monthly on the same schedule as IDB. Data values exist for cases endorsed starting in 2003.

default - The Default Data Mart provides case level information on cases that are 30-, 60- or 90-days delinquent. This data mart was enhanced during the November 2006 refresh, adding many new columns that reflect the change in reporting by the servicing lenders. The tables, default\_episodes, sfdw\_default\_history and sfdw\_default\_current\_detail are refreshed monthly, typically on the 9th working day of the month.

sfdw\_default\_history - This table contains case level historical data, reported by the lender, which reflects everything that happens during a default episode, whether it is a loss mitigation engagement, a first legal action to foreclose, the start of the pre-foreclosure sale process, etc. The data in this table is refreshed on the 9th working day of each month and may contain multiple records for a case and is provided by the SFDMS/F42D.

default\_episode - This table provides case level default data. An episode is either one complete cycle of a case going into default then coming out of default or a case which is in active default status. This table may contain multiple records for a case and is refreshed on the 9th working day of each month.

sfdw\_default\_current\_detail - This table contains case level default data reflecting the last occurrence of default for a case. This table is refreshed on the 9th working day of each month and contains only one record for each case.

loss\_mitigation - A case level information provided weekly for the three Loss Mitigation Retention claim types: Special Forbearance, Mortgage Modification; and Partial Claim.

loan\_modification - This structure contains case level data for incentivized and non-incentivized loan modifications. The data are refreshed weekly

lossmit\_costs - Derived table based on the loss\_mitigation table and idb\_1. Used to obtain mitigation claim amounts.

claims\_601\_case\_dta - This table contains data to support the accelerated claims disposition programs.

sams\_case\_record - This is a Union between sams\_monthly\_record and sams\_archive\_record and is refreshed the 1st week of each month. It is used to determine the status of conveyances, the capital/income expense amounts, the sales and real estate owned (REO) expenses and sales proceeds to FHA.

fannie\_fico\_pre2004 - A derived database used to provide supplemental credit data. Not a component of the SFDW but based on research conducted by HUD and other parties and provided to ITDC for use in this study.

unicon\_fico - A derived database used to provide supplemental credit data. Not a component of the SFDW but based on research conducted by HUD and other parties and provided to ITDC for use in this study.

## B. Model Sensitivity to Economic Projections

Three critical economic variables used in making these projections are future house prices, interest rates, and unemployment rates. We conducted a sensitivity analysis to examine how the Fund's economic net worth may change with these macroeconomic factors to gain insights into the possible magnitude of the impacts. Specifically, we investigated the changes in economic net worth by applying the four alternative combinations of percentile paths outlined previously. The benchmark for these sensitivity tests is the deterministic base case, using the FY 2026 Mid-Session Review of the President's Economic Assumptions.

Recent circumstances suggest that the alternative projections should not be expected to yield dramatically different results from the PEA baseline. Mortgage interest rates have been at historically low levels since FY 2012 and reached their lowest values as recently as FY 2021. Rates have since risen rapidly in response to anti-inflationary actions by the Federal Reserve, roughly doubling over a two-year period. The mandated PEA assumptions applied as the baseline scenario in our analysis stipulate that mortgage rates will generally decline over the next 10 years.

To allow for variation around this likelihood, our analysis applies four alternative scenarios for mortgage interest rates, treasury rates, unemployment rates, and housing prices to examine the potential impact on portfolio performance. Alternative scenarios that lead to even higher interest rates than the PEA will only further reduce prepayment speeds on outstanding loans; a substantial decline in interest rates would be required to precipitate a refinance boom among current borrowers with historically low-rate mortgages associated with the widely noted "lock-in" effect, incentivizing homeowners to remain in their homes rather than incurring costs associated with higher current mortgage rates.

## C. Changing Market Landscape

In the aftermath of the COVID-19 pandemic and the wind-down of fiscal and monetary stimulus, mortgage interest rates rose rapidly from as low as 3 percent to 7 percent in late 2022. Since that

time, they have fluctuated within a range of 6-8%, currently standing at approximately 7% as of mid-2025. The inventory of homes for sale has improved, especially in the West and South, reaching 31.5 percent as of May 2025, a post-pandemic high, but still below pre-pandemic levels. Home prices have continued to rise, although more slowly than during the pandemic period.<sup>71</sup>

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<sup>71</sup> National Association of Realtors [April 2025 Monthly Housing Market Trends Report](#).

## Acknowledgement

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## Appendix A. Data Reconciliation

### A1. Data Sources

In our analysis, we have relied on data from FHA, Moody's, and the OMB.

From FHA, we have received the following data:

1. Claims\_601\_Case\_Data: used for the cash entry from note sales
2. IDB: core case data; this table is derived based on fields from IDB\_1, IDB\_2, IDB\_3 and the Decision\_FICO\_Score (one file each for 1975 – 2025)
3. Lossmit\_Costs: derived table based on the Loss Mitigation table and IDB\_1, used to obtain mitigation claim amounts
4. Sams\_case\_record: used to determine the status of the conveyances, the capital income/expense amounts, the sales and REO expenses, and sales proceeds to FHA, where applicable
5. SFDW\_Default\_History: used to create period information related to default histories
6. Fannie\_FICO\_pre2004: used for supplemental credit data
7. Current\_Status: table displaying the current status of each loan

From OMB, we have received the Economic Assumptions for the PEA. The economic data that is included in the analysis is shown below:

8. HPI
9. Mortgage rates
10. Treasury rates
11. Unemployment rates

The following historical series are obtained from Moody's' Economy.com

12. FHFA house price indices
13. BLS household unemployment rates
14. FHLMC mortgage rates
15. Census median home prices
16. Treasury yields

### A2. Data Processing – Mortgage Level Modeling

Starting with the raw data, ITDC developed datasets for the mortgage level transition and loss severity models. The first step in preparing the data for analysis was the processing of the economic data. Historical economic data was imported by quarter, additional data elements were derived, and data was joined to the FHA mortgage data.

Once the economic data was prepared, the core data processing occurred. We used mortgage-level data to reconstruct quarterly mortgage-event histories by relating mortgage origination information to other data reflecting events that occurred over the history of the mortgage. In the process of creating quarterly event histories, each mortgage contributed an observed transition for every quarter from origination up to and including the period of mortgage termination, or until the end of 2025, if the mortgage remained active.

### A3. Data Reconciliation

Data reconciliation is a very important step to ensure the accuracy of the model and the estimation results. To reconcile the data processed with the data provided by FHA, we compared summaries of key data elements with the summaries provided by FHA. The summaries for the number of active mortgages, IIF, number of 90-day delinquencies, and the number of claims to date are shown in the following tables, Exhibit A-1 through A-4. Most of the data processed matches the FHA data totals, with differences centered on early years. The reconciliation tables are based on data as of September 2025.

Exhibit A-1 Data Reconciliation for Number of Active Loans<sup>72</sup>

| Credit Subsidy Cohort | Federal Housing Administration (Data as of September 2025) | Independent Actuary | Difference (Actuary - FHA) | Percent Difference (Actuary - FHA) / FHA |
|-----------------------|------------------------------------------------------------|---------------------|----------------------------|------------------------------------------|
| 1996                  | 9,481                                                      | 9,481               | -                          | 0.00%                                    |
| 1997                  | 13,148                                                     | 13,148              | -                          | 0.00%                                    |
| 1998                  | 21,324                                                     | 21,324              | -                          | 0.00%                                    |
| 1999                  | 28,540                                                     | 28,540              | -                          | 0.00%                                    |
| 2000                  | 17,377                                                     | 17,377              | -                          | 0.00%                                    |
| 2001                  | 29,669                                                     | 29,669              | -                          | 0.00%                                    |
| 2002                  | 42,492                                                     | 42,492              | -                          | 0.00%                                    |
| 2003                  | 58,881                                                     | 58,881              | -                          | 0.00%                                    |
| 2004                  | 74,371                                                     | 74,371              | -                          | 0.00%                                    |
| 2005                  | 54,308                                                     | 54,308              | -                          | 0.00%                                    |
| 2006                  | 44,455                                                     | 44,455              | -                          | 0.00%                                    |
| 2007                  | 43,399                                                     | 43,399              | -                          | 0.00%                                    |
| 2008                  | 97,239                                                     | 97,239              | -                          | 0.00%                                    |
| 2009                  | 192,054                                                    | 192,054             | -                          | 0.00%                                    |
| 2010                  | 227,017                                                    | 227,017             | -                          | 0.00%                                    |
| 2011                  | 184,275                                                    | 184,275             | -                          | 0.00%                                    |
| 2012                  | 239,209                                                    | 239,209             | -                          | 0.00%                                    |
| 2013                  | 342,783                                                    | 342,783             | -                          | 0.00%                                    |
| 2014                  | 143,216                                                    | 143,216             | -                          | 0.00%                                    |
| 2015                  | 241,438                                                    | 241,438             | -                          | 0.00%                                    |
| 2016                  | 340,831                                                    | 340,831             | -                          | 0.00%                                    |
| 2017                  | 375,357                                                    | 375,357             | -                          | 0.00%                                    |
| 2018                  | 302,373                                                    | 302,373             | -                          | 0.00%                                    |
| 2019                  | 304,637                                                    | 304,637             | -                          | 0.00%                                    |
| 2020                  | 620,764                                                    | 620,764             | -                          | 0.00%                                    |
| 2021                  | 1,056,099                                                  | 1,056,099           | -                          | 0.00%                                    |
| 2022                  | 842,490                                                    | 842,490             | -                          | 0.00%                                    |
| 2023                  | 624,580                                                    | 624,580             | -                          | 0.00%                                    |
| 2024                  | 673,386                                                    | 673,386             | -                          | 0.00%                                    |
| 2025                  | 848,422                                                    | 866,595             | 18,173                     | 2.14%                                    |
| Total                 | 8,095,776                                                  | 8,111,788           | 18,173                     | 0.22%                                    |

<sup>72</sup> Source: SFDW.IDB\_1.

Exhibit A-2 Data Reconciliation for Insurance in Force

| Credit Subsidy Cohort | Federal Housing Administration (Data as of September 2025) | Independent Actuary | Difference (Actuary - FHA) | Percent Difference (Actuary - FHA) / FHA |
|-----------------------|------------------------------------------------------------|---------------------|----------------------------|------------------------------------------|
| 1996                  | 650,989,900                                                | 650,989,900         | -                          | 0.00%                                    |
| 1997                  | 908,471,488                                                | 908,471,488         | -                          | 0.00%                                    |
| 1998                  | 1,586,924,186                                              | 1,586,924,186       | -                          | 0.00%                                    |
| 1999                  | 2,221,592,719                                              | 2,221,592,719       | -                          | 0.00%                                    |
| 2000                  | 1,331,120,474                                              | 1,331,120,474       | -                          | 0.00%                                    |
| 2001                  | 2,560,689,224                                              | 2,560,689,224       | -                          | 0.00%                                    |
| 2002                  | 3,972,837,863                                              | 3,972,837,863       | -                          | 0.00%                                    |
| 2003                  | 6,212,091,292                                              | 6,212,091,292       | -                          | 0.00%                                    |
| 2004                  | 7,872,520,054                                              | 7,872,520,054       | -                          | 0.00%                                    |
| 2005                  | 5,878,662,156                                              | 5,878,662,156       | -                          | 0.00%                                    |
| 2006                  | 5,054,292,477                                              | 5,054,292,477       | -                          | 0.00%                                    |
| 2007                  | 5,316,095,856                                              | 5,316,095,856       | -                          | 0.00%                                    |
| 2008                  | 13,665,107,997                                             | 13,665,107,997      | -                          | 0.00%                                    |
| 2009                  | 29,181,952,240                                             | 29,181,952,240      | -                          | 0.00%                                    |
| 2010                  | 33,292,682,119                                             | 33,292,682,119      | -                          | 0.00%                                    |
| 2011                  | 27,428,769,172                                             | 27,428,769,172      | -                          | 0.00%                                    |
| 2012                  | 36,687,385,498                                             | 36,687,385,498      | -                          | 0.00%                                    |
| 2013                  | 54,395,749,281                                             | 54,395,749,281      | -                          | 0.00%                                    |
| 2014                  | 19,249,855,370                                             | 19,249,855,370      | -                          | 0.00%                                    |
| 2015                  | 37,836,189,516                                             | 37,836,189,516      | -                          | 0.00%                                    |
| 2016                  | 57,286,018,294                                             | 57,286,018,294      | -                          | 0.00%                                    |
| 2017                  | 66,313,478,176                                             | 66,313,478,176      | -                          | 0.00%                                    |
| 2018                  | 54,130,881,015                                             | 54,130,881,015      | -                          | 0.00%                                    |
| 2019                  | 57,613,515,089                                             | 57,613,515,089      | -                          | 0.00%                                    |
| 2020                  | 136,030,860,196                                            | 136,030,860,196     | -                          | 0.00%                                    |
| 2021                  | 253,620,653,169                                            | 253,620,653,169     | -                          | 0.00%                                    |
| 2022                  | 222,515,390,023                                            | 222,515,390,023     | -                          | 0.00%                                    |
| 2023                  | 178,545,039,597                                            | 178,545,039,597     | -                          | 0.00%                                    |
| 2024                  | 202,532,255,722                                            | 202,532,255,722     | -                          | 0.00%                                    |
| 2025                  | 266,243,815,928                                            | 271,797,125,154     | 5,553,309,226              | 2.09%                                    |
| Total                 | 1,790,281,412,477                                          | 1,795,689,195,317   | 5,553,309,226              | 0.31%                                    |

Exhibit A-3 Data Reconciliation for Number of 90 Day Delinquencies

| Credit Subsidy Cohort | Federal Housing Administration (Data as of September 2025) | Independent Actuary | Difference (Actuary - FHA) | Percent Difference (Actuary - FHA) / FHA |
|-----------------------|------------------------------------------------------------|---------------------|----------------------------|------------------------------------------|
| 1996                  | 534                                                        | 535                 | 1                          | 0.19%                                    |
| 1997                  | 600                                                        | 602                 | 2                          | 0.33%                                    |
| 1998                  | 924                                                        | 926                 | 2                          | 0.22%                                    |
| 1999                  | 1,196                                                      | 1,199               | 3                          | 0.25%                                    |
| 2000                  | 923                                                        | 926                 | 3                          | 0.33%                                    |
| 2001                  | 1,439                                                      | 1,443               | 4                          | 0.28%                                    |
| 2002                  | 1,755                                                      | 1,764               | 9                          | 0.51%                                    |
| 2003                  | 2,301                                                      | 2,310               | 9                          | 0.39%                                    |
| 2004                  | 3,141                                                      | 3,157               | 16                         | 0.51%                                    |
| 2005                  | 2,620                                                      | 2,632               | 12                         | 0.46%                                    |
| 2006                  | 2,333                                                      | 2,348               | 15                         | 0.64%                                    |
| 2007                  | 2,644                                                      | 2,658               | 14                         | 0.53%                                    |
| 2008                  | 5,968                                                      | 5,997               | 29                         | 0.49%                                    |
| 2009                  | 8,315                                                      | 8,352               | 37                         | 0.44%                                    |
| 2010                  | 8,165                                                      | 8,203               | 38                         | 0.47%                                    |
| 2011                  | 5,634                                                      | 5,654               | 20                         | 0.35%                                    |
| 2012                  | 6,006                                                      | 6,040               | 34                         | 0.57%                                    |
| 2013                  | 6,978                                                      | 7,020               | 42                         | 0.60%                                    |
| 2014                  | 5,807                                                      | 5,838               | 31                         | 0.53%                                    |
| 2015                  | 9,807                                                      | 9,886               | 79                         | 0.81%                                    |
| 2016                  | 13,775                                                     | 13,939              | 164                        | 1.19%                                    |
| 2017                  | 17,020                                                     | 17,253              | 233                        | 1.37%                                    |
| 2018                  | 19,111                                                     | 19,433              | 322                        | 1.68%                                    |
| 2019                  | 21,817                                                     | 22,271              | 454                        | 2.08%                                    |
| 2020                  | 28,449                                                     | 29,192              | 743                        | 2.61%                                    |
| 2021                  | 43,542                                                     | 45,075              | 1533                       | 3.52%                                    |
| 2022                  | 51,227                                                     | 53,062              | 1835                       | 3.58%                                    |
| 2023                  | 40,732                                                     | 41,314              | 582                        | 1.43%                                    |
| 2024                  | 28,366                                                     | 28,581              | 215                        | 0.76%                                    |
| 2025                  | 8,758                                                      | 8,818               | 60                         | 0.69%                                    |
| Total                 | 349,887                                                    | 356,428             | 6,541                      | 1.87%                                    |

Exhibit A-4 Data Reconciliation for Number of Claims to Date<sup>73</sup>

| Credit Subsidy Cohort | Federal Housing Administration (Data as of September 2025) | Independent Actuary | Difference (Actuary - FHA) | Percent Difference (Actuary - FHA) / FHA |
|-----------------------|------------------------------------------------------------|---------------------|----------------------------|------------------------------------------|
| 1996                  | 63,626                                                     | 63,626              | -                          | 0.00%                                    |
| 1997                  | 60,071                                                     | 60,071              | -                          | 0.00%                                    |
| 1998                  | 67,817                                                     | 67,817              | -                          | 0.00%                                    |
| 1999                  | 84,691                                                     | 84,691              | -                          | 0.00%                                    |
| 2000                  | 71,685                                                     | 71,685              | -                          | 0.00%                                    |
| 2001                  | 85,921                                                     | 85,921              | -                          | 0.00%                                    |
| 2002                  | 91,251                                                     | 91,251              | -                          | 0.00%                                    |
| 2003                  | 92,047                                                     | 92,047              | -                          | 0.00%                                    |
| 2004                  | 117,079                                                    | 117,079             | -                          | 0.00%                                    |
| 2005                  | 93,201                                                     | 93,201              | -                          | 0.00%                                    |
| 2006                  | 95,579                                                     | 95,579              | -                          | 0.00%                                    |
| 2007                  | 107,894                                                    | 107,894             | -                          | 0.00%                                    |
| 2008                  | 227,497                                                    | 227,497             | -                          | 0.00%                                    |
| 2009                  | 230,682                                                    | 230,682             | -                          | 0.00%                                    |
| 2010                  | 119,204                                                    | 119,204             | -                          | 0.00%                                    |
| 2011                  | 49,691                                                     | 49,691              | -                          | 0.00%                                    |
| 2012                  | 31,553                                                     | 31,553              | -                          | 0.00%                                    |
| 2013                  | 29,925                                                     | 29,925              | -                          | 0.00%                                    |
| 2014                  | 18,005                                                     | 18,005              | -                          | 0.00%                                    |
| 2015                  | 18,671                                                     | 18,671              | -                          | 0.00%                                    |
| 2016                  | 17,336                                                     | 17,336              | -                          | 0.00%                                    |
| 2017                  | 14,282                                                     | 14,282              | -                          | 0.00%                                    |
| 2018                  | 10,244                                                     | 10,244              | -                          | 0.00%                                    |
| 2019                  | 6,486                                                      | 6,486               | -                          | 0.00%                                    |
| 2020                  | 4,124                                                      | 4,124               | -                          | 0.00%                                    |
| 2021                  | 4,350                                                      | 4,350               | -                          | 0.00%                                    |
| 2022                  | 5,095                                                      | 5,095               | -                          | 0.00%                                    |
| 2023                  | 2,558                                                      | 2,558               | -                          | 0.00%                                    |
| 2024                  | 487                                                        | 487                 | -                          | 0.00%                                    |
| 2025                  | 6                                                          | 6                   | -                          | 0.00%                                    |
| Total                 | 1,865,811                                                  | 1,821,058           | 0                          | 0.00%                                    |

<sup>73</sup> Source: SFDW.IDB\_1.

## Appendix B. Econometric Analysis of Mortgage Status Transitions and Terminations

### B1. Model Specification and Estimation

#### B1.1. Specification of FHA Mortgage Status Transition and Termination Models

Actuarial Reviews before the FY 2010 analysis applied a competing risk framework based on multinomial logit models for quarterly conditional probabilities of prepayment and claim terminations. The general approach was based on the multinomial logit models reported by Calhoun and Deng (2002), initially developed for application to the Office of Federal Housing Enterprise Oversight (OFHEO) and Federal Housing Finance Agency (FHFA) risk-based capital adequacy tests for Fannie Mae and Freddie Mac. The multinomial model recognized the competing-risks nature of prepayment and claim terminations.

Starting in FY 2010, the modeling utilized FHA historical data on new 90-day default episodes on outstanding mortgages beginning with FY 1990 Q1 originations. The date at which a loan is first reported to be 90 or more days in arrears is used to define the start of a 90-day default episode, which continues until the default episode ends in a cure (i.e., becoming current once again) or the loan terminates through claim or prepayment. Under this approach, loans that start a quarter in 90 days or more delinquent are deemed to be in default status at the beginning of that quarter. Similarly, active loans not in a 90-day default episode at the beginning of the quarter are classified as current. Thus, a new default event (NDE) marking the entry into 90-day default status occurs during the quarter preceding the quarter the loan is first assigned to default status (i.e., begins the quarter in default status). Claims, prepayments, and streamlined refinancings comprise terminal events occurring within a quarter that result in the removal of the loan from the outstanding book of business at the start of the next quarter.

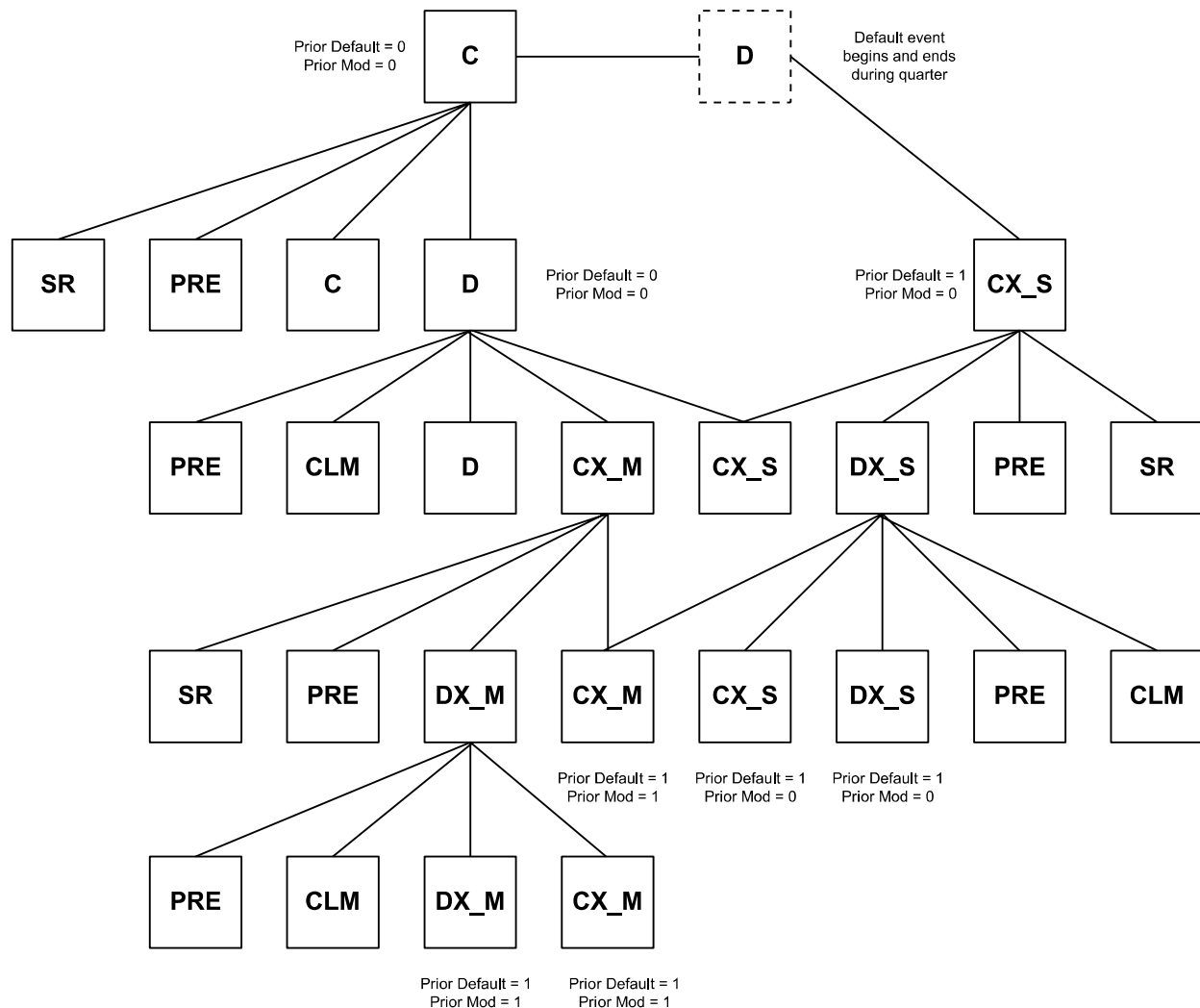
We have used the data on 90-day default episodes to develop and apply a greatly expanded status transition approach that extends the analysis to an eight-transition equation framework. This includes modeling transitions from current-to-default to default to current while accounting for the prior occurrence of any default or cure events. Indicators of prior default and prior mod-cure are included as additional explanatory variables in the transition models to further control for the initial conditions of each loan, but without having to expand the number of equations to be estimated. At the same time, it expands the state-space used in performing the actuarial calculations to reflect better differences in behavior associated with path dependence.

Exhibit B-1 summarizes the loan status transitions we modeled for the FY 2025 review. As described above, we track loans with and without prior default episodes and with and without prior self- or mod-cures as separate loan status categories to introduce path dependence into the analysis. We also account for duration dependence in transition rates by controlling for the duration of default for loans in default status and the duration of cure for loans in self-cure or mod-cure status.



Exhibit B-1 illustrates how the statuses emerge as loan proceeds period-by-period (row-by-row in the figure). However, it is not intended to show all possible transitions that could occur each time for readability purposes. For example, the figure shows the transition from C to D in rows 1 and 2, and then all possible transitions from D to D, D to CX\_S, D to CLM, and D to PRE in rows 2 and 3, but to preserve clarity does not subsequently repeat transitions from status D in rows 3 and 4. We do not repeat those transitions in the figure once we show the statuses to which any given status may lead.

Exhibit B-1: Loan Status Transitions Framework



Next, we will discuss the interpretation of each loan status, and the associated transitions represented in Exhibit B-1.

#### Initial Status Current C: Current with No Prior Default or Prior Mod

Loans originating in current status (C) can continue in current status (C), transition to default status (D), or terminate as a claim (CLM) or prepayment (PRE). In addition, we allow for the possibility that an initially current loan starts a 90-day default status during the quarter but self-cures to become current again before the start of the next quarter. These loans are considered to have transitioned to a new status CX\_S, defined as a loan with a prior default that has self-cured. We model these transitions as a distinct competing-risk for loans initially in status C. Note that this is a by-product of using 90-day default to track non-performance. A monthly model would include separate transitions from C to D and D to CX\_S. This highlights the critical distinction between a new default “event” (NDE) that starts a 90-day default episode and a current-to-default “transition,” which corresponds to the change in status at the start of one quarter versus the status occupied at the start of the next quarter.

#### Initial Status D: Default with No Prior Default or Prior Mod

Loans initially in default status D, having no default or prior mod, return to cured status along two possible paths, depending on whether they self-cure (CX\_S) or cure with a loan modification (CX\_M). In addition, these loans may remain in default status (D) or terminate in a claim (CLM) or prepayment (PRE). Termination as a streamline refinance (SR) from default status (D) is not allowed under FHA guidelines.

#### Initial Status CX\_S: Current with Prior Default and No Prior Mod-Cure

Loans that have self-cured (CX\_S) may remain in that status, transition back to default as loans now having both a prior default and self-cure (DX\_S), or terminate as prepayment (PRE) or streamline refinance (SR). We note that current loans with a prior default may be allowed to streamline refinance if there has been sufficient time since the default. We control statistical modeling for the length of time since the preceding default was cured. As discussed above, this status is somewhat unique in that it may be reached directly from current status C and default statuses D and DX\_S. Once reached, the status is distinguished by having had a prior default episode.

#### Initial Status CX\_M: Current with Prior Default and Prior Mod-Cure

Current loans that have had one-or-more prior defaults and at least one mod-cure (CX\_M) may remain in that status, transition back to default (DX\_M), or terminate as prepayment (PRE) or streamline refinance (SR). It is important to emphasize that our prior default and mod indicators

correspond to “one or more prior defaults” and “one or more prior mods.” Thus, CX\_M does not necessarily describe the most recent cure type for loans with multiple cures status. Conversely, self-cure status (CX\_S) only applies when all prior defaults are self-cured, and there has been no prior mod-cure.

### Initial Status DX\_S: Default with Prior Default and No Prior Mod-Cure

Loans in default having one-or-more prior defaults that all self-cured (DX\_S) may remain in that status, cured again by either self-cure (CX\_S) or mod-cure (CX\_M), or terminate as prepayment (PRE) or claim (CLM). As noted above, for loans in status DX\_S, we know that all prior cures were self-cures.

### Graphic Illustrations of the Timeline of Status Transitions

Exhibit B-2 is provided to illuminate further how the default episode data contributes to identifying observed default and cure transitions for modeling loan performance through a series of examples.

Example 1 corresponds to the occurrence of a new default event (NDE) to a loan initially in current status C and the subsequent transition of the defaulted (D) loan to claim (CLM).

Example 2 shows a current loan with no prior default or loan mod (status C) transitioning to default (D), remaining in default status for one complete quarter, and then transitioning back to current status (CX\_M) after a loan modification.

Example 3 starts with a previously defaulted and self-cured loan spending four quarters in current status (CX\_S), defaulting again, and remaining in default status DX\_S for one quarter before terminating in prepayment (PRE).

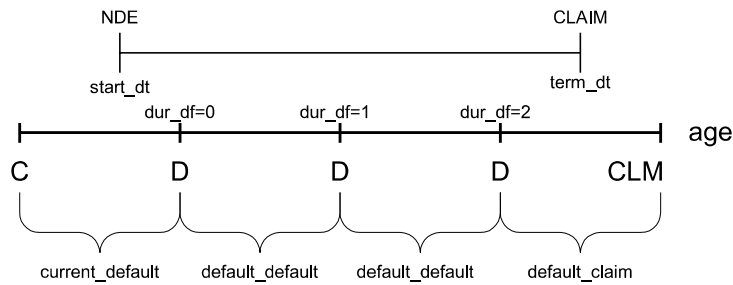
Example 4 has a recently mod-cured loan in current status (CX\_M) defaulting again and remaining in default status DX\_M until the historical sample ends. This results in the censoring of that default episode, so we do not yet know how long the episode will continue or the ultimate status of the loan.

Example 5 includes the case of a current loan with no prior default or prior mod (C) entering 90-day default status (NDE) but quickly self-curing to return to current status (CX\_S) by the end of the same quarter.

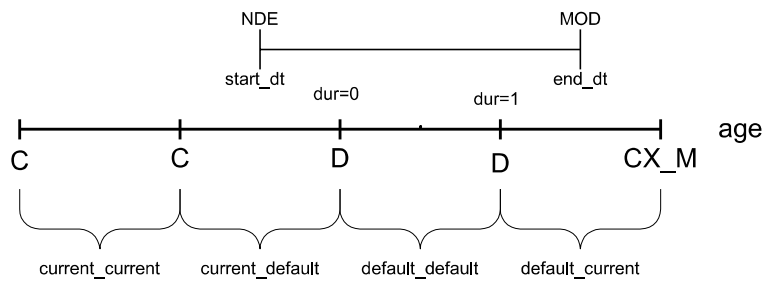
These examples are intended to illustrate the observational scheme used to define the loan status transition framework in Exhibit B-1 and do not exhaust all the possible loan transitions one might observe or the varying timing of these transitions. They highlight the distinction between transitions associated with period-to-period changes in loan status and loan termination, either through prepayment or claim, which ends the sequence of transitions for an individual loan.

Exhibit B-2: Examples of Loan Transition Types

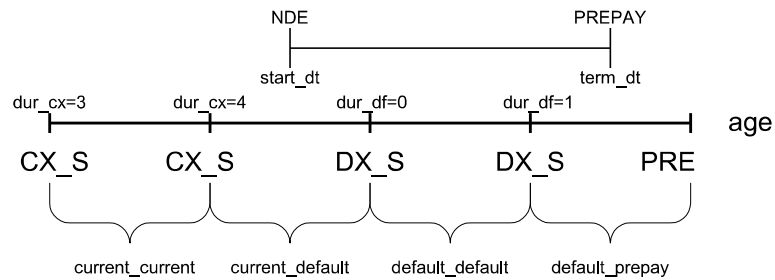
Example 1 : C to D / D to CLM



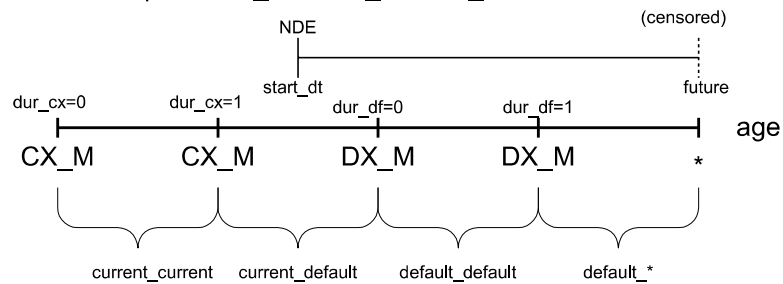
Example 2 : C to D / D to CX\_M



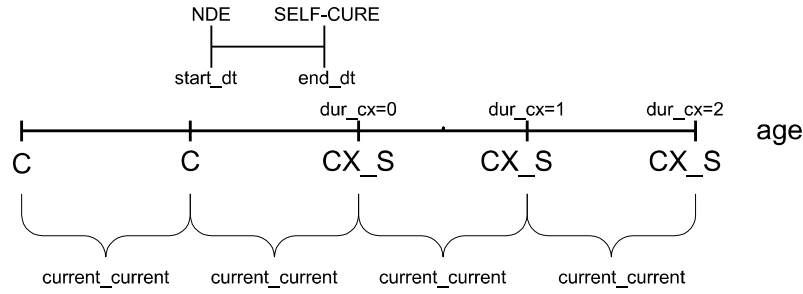
Example 3: CX\_S to DX\_S / DX\_S to PRE



Example 4: CX\_M to DX\_M / DX\_M to Censored



### Example 5 : C to CX\_S



## B1.2. Specification of Multinomial Logit Models

The status transition framework results in two sets of competing risks: one for loans in current status and one for loans in default status. For loans current at the start of the quarter, the competing risks are prepayment through Non-Streamlined Refinance (NSR) or Streamlined Refinance (SR), transition to default status, or remaining current (either without any modification or got modified and remained current within the same quarter). The competing risks for loans in default status at the start of the quarter are claim, prepayment, or transition to current status through self-cure or modification or continuing in the default state. This gives rise to 10 possible transitions and their corresponding probabilities (i.e. 5 transitions each for transitions from current and default) requiring estimation for 8 independent binomial logits (i.e. 4 binomial logits each for transitions from current and default). Therefore, for each of the six loan products, there are 48 logit models.

The starting point for specification of the loan performance models is multinomial logit models of quarterly conditional probabilities for transitions from current to prepayment (streamlined or non-streamlined refinance), default, or remaining current, and for transitions from default to claim, prepayment, back to current (self-cured or modified cure), or continuing in the default state. The corresponding mathematical expressions for the conditional probabilities for loans starting in current status in quarter  $t$  and transitioning to prepay, default, or remaining current, in the subsequent quarter  $t + 1$  are given by:

$$\mathbf{B}_{DEF}^{CUR} = (\beta_0^{CUR\_DEF}, \beta_1^{CUR\_DEF}, \dots, \beta_k^{CUR\_DEF}); \mathbf{X} = (\mathbf{1}_n, \mathbf{X}_1, \dots, \mathbf{X}_k)^T$$

Where  $\mathbf{X}_i = (\mathbf{X}_{i1}, \mathbf{X}_{i2}, \dots, \mathbf{X}_{in})^T$ ,  $n$  : number of observations;  $\mathbf{X}$  = Extended design matrix of explanatory variables.

$$\mathbf{B} = \{\mathbf{B}_{DEF}^{CUR}, \mathbf{B}_{PRE\_NSR}^{CUR}, \mathbf{B}_{PRE\_SR}^{CUR}, \mathbf{B}_{CUR\_X}^{CUR}\}$$

Here the transition  $CUR\_CUR$  is the baseline category.

In general,  $B_j^i = (\beta_0^{i,j}, \beta_1^{i,j}, \dots, \beta_k^{i,j})$ , where  $i \rightarrow j$  in the superscript is the transitioning from state  $i$  to state  $j$ .

Here  $i$  is  $CUR$  and  $j \in \{DEF, PRE\_NSR, PRE\_SR, CUR\_X\}$

It is to be noted that  $CLM$ ,  $CUR\_S$ ,  $CUR\_M$  will be talked about later in the section when all transitions from default state will be dealt with. Also, the vector  $X$  is different for loans transitioning from current and default state.

$$\pi_{DEF}^{CUR}(t | X) = \frac{\exp(B_{DEF}^{CUR}X)}{1 + \sum_{\forall B} \exp(BX)} \quad (1a)$$

$$\pi_{CUR\_X}^{CUR}(t | X) = \frac{\exp(B_{CUR\_X}^{CUR}X)}{1 + \sum_{\forall B} \exp(BX)} \quad (1b)$$

$$\pi_{PRE\_NSR}^{CUR}(t | X) = \frac{\exp(B_{PRE\_NSR}^{CUR}X)}{1 + \sum_{\forall B} \exp(BX)} \quad (1c)$$

$$\pi_{PRE\_SR}^{CUR}(t | X) = \frac{\exp(B_{PRE\_SR}^{CUR}X)}{1 + \sum_{\forall B} \exp(BX)} \quad (1d)$$

Note: The probability of the baseline category has not been calculated as it is just the one minus the rest of the probabilities. This has been followed for both types of loans that started from current and default states as the initial state.

The corresponding equations for loans started in default status in quarter  $t$  and transitioning to claim, prepay, current with self-cure, current with mod-cure, or remaining in default, respectively, in the subsequent quarter  $t + 1$  are given by are:

Here  $B = \{B_{PRE}^{DEF}, B_{CUR\_S}^{DEF}, B_{CUR\_M}^{DEF}, B_{CLM}^{DEF}\}$ , and  $DEF\_DEF$  is the baseline category.

$$\pi_{PRE}^{DEF}(t | X) = \frac{\exp(B_{PRE}^{DEF}X)}{1 + \sum_{\forall B} \exp(BX)} \quad (2a)$$

$$\pi_{CUR\_S}^{DEF}(t | X) = \frac{\exp(B_{CUR\_S}^{DEF}X)}{1 + \sum_{\forall B} \exp(BX)} \quad (2b)$$

$$\pi_{CUR\_M}^{DEF}(t | X) = \frac{\exp(B_{CUR\_M}^{DEF}X)}{1 + \sum_{\forall B} \exp(BX)} \quad (2c)$$

$$\pi_{CLM}^{DEF}(t | X) = \frac{\exp(B_{CLM}^{DEF}X)}{1 + \sum_{\forall B} \exp(BX)} \quad (2d)$$

The coefficient vectors  $B_j^i$  are the unknown parameters to be estimated for the multinomial logit model for initial status  $i$  indicating current (CUR) or default (DEF) and ending status  $j$  indicating prepayment (PRE\_NSR or PRE\_SR), default (DEF), or current (CUR) when  $i$  is current, and  $j$  is prepayment (PRE), current (CUR\_S or CUR\_M), or claim (CLM) when  $i$  is default. It is important to note that  $j$  is not CUR when  $i$  is CUR and  $j$  is not DEF when  $i$  is DEF, because CUR\_CUR and

DEF\_DEF are baseline categories for transitions starting from CUR and DEF respectively. We denote by  $X$  the vector of explanatory variables for the conditional probability of transitioning from starting status CUR and DEF. Some components of  $X$  are constant over the life of the loan and therefore do not vary with time. The “dynamic” or time-varying explanatory components (variables) of  $X$  include mortgage age, the duration of the default episode for loans in default status, and the duration of cure for current loans with a prior default. They also include an array of time-varying economic factors that predict default, prepay, cure, and claim, which will be described in detail below.

As illustrated in Exhibit B-1, for the FY 2025 review actuarial projections, we ultimately stratify initial current status (CUR) by whether the loan has had a prior default or prior mod (or both). As discussed further below, the econometric equations (1a) - (1d) and (3.1a) - (3.2c) for loans in current statuses (C, CX\_S, CX\_M) presented above were jointly estimated using pooled samples of loans with and without prior default episodes and prior loan modifications, and the explanatory variables in  $X$  include indicators (dummy variables) for prior events.

### B1.3. Computation of Multinomial Logit Probabilities from Binomial Logit Parameters

As in prior-year reviews, we apply an approach first proposed by Begg and Gray (1984), in which we estimate separate independent binomial logit models for each possible transition type and then recombine the estimates to derive multinomial logit probabilities. Begg and Gray (1984) applied Bayes Law for conditional probabilities to demonstrate that the values of parameters  $B$  estimated from separate independent binomial logit (BNL) models are parametrically equivalent to those for the corresponding multinomial logit (MNL). Here we have 4 BNL models for loans in current status at the start of quarter  $t$ , the pairs in each of the 4 BNL are (CUR\_DEF, CUR\_CUR), (CUR\_PRE\_NSR, CUR\_CUR), (CUR\_PRE\_SR, CUR\_CUR), and (CUR\_CUR\_X, CUR\_CUR). Here  $C$  in the below equations is equivalent  $B$  in MNL.

Hence,

For Binomial Model 1, we have

$$\Pi_{DEF}^{CUR}(t | X) = \frac{\exp(C_{DEF}^{CUR}X)}{1 + \exp(C_{DEF}^{CUR}X)} \quad (3.1a)$$

$$\Pi_{CUR}^{CUR}(t | X) = \frac{1}{1 + \exp(C_{DEF}^{CUR}X)} \quad (3.2a)$$

The  $C_{DEF}^{CUR}$  computed from this binomial model will be substituted for  $B_{DEF}^{CUR}$  in multinomial logit model in (1a)

For Binomial Model 2, we have



$$\Pi_{CUR\_X}^{CUR}(t | X) = \frac{\exp(C_{CUR\_X}^{CUR}X)}{1 + \exp(C_{CUR\_X}^{CUR}X)} \quad (3.1b)$$

$$\Pi_{CUR}^{CUR}(t | X) = \frac{1}{1 + \exp(C_{CUR\_X}^{CUR}X)} \quad (3.2b)$$

The  $C_{CUR\_X}^{CUR}$  computed from this binomial model will be substituted for  $B_{CUR\_X}^{CUR}$  in multinomial logit model in (1b)

For Binomial Model 3, we have

$$\Pi_{PRE\_NSR}^{CUR}(t | X) = \frac{\exp(C_{PRE\_NSR}^{CUR}X)}{1 + \exp(C_{PRE\_NSR}^{CUR}X)} \quad (3.1c)$$

$$\Pi_{CUR}^{CUR}(t | X) = \frac{1}{1 + \exp(C_{PRE\_NSR}^{CUR}X)} \quad (3.2c)$$

The  $C_{PRE\_NSR}^{CUR}$  computed from this binomial model will be substituted for  $B_{PRE\_NSR}^{CUR}$  in multinomial logit model in (1c)

For Binomial Model 4, we have

$$\Pi_{PRE\_SR}^{CUR}(t | X) = \frac{\exp(C_{PRE\_SR}^{CUR}X)}{1 + \exp(C_{PRE\_SR}^{CUR}X)} \quad (3.1d)$$

$$\Pi_{CUR}^{CUR}(t | X) = \frac{1}{1 + \exp(C_{PRE\_SR}^{CUR}X)} \quad (3.2d)$$

The  $C_{PRE\_SR}^{CUR}$  computed from this binomial model will be substituted for  $B_{PRE\_SR}^{CUR}$  in multinomial logit model in (1d)

We used an upper-case  $\Pi$  to indicate the binomial logit probability and distinguish it from the lower-case  $\pi$  used above to denote the multinomial logit probabilities. Here, again we have 4 BNL models for loans in default status at the start of quarter  $t$ , the pair in each of the 4 BNL are (DEF\_PRE, DEF\_DEF), (DEF\_CUR\_S, DEF\_DEF), (DEF\_CUR\_M, DEF\_CLM), and (DEF\_CLM, DEF\_DEF). The corresponding binomial probabilities for transitions from default status to claim, prepayment, current (self-cure or modified cure), or remaining in default status are given by:

For Binomial Model 5, we have

$$\Pi_{PRE}^{DEF}(t | X) = \frac{\exp(C_{PRE}^{DEF}X)}{1 + \exp(C_{PRE}^{DEF}X)} \quad (4.1a)$$

$$\Pi_{DEF}^{DEF}(t | X) = \frac{1}{1 + \exp(C_{PRE}^{DEF}X)} \quad (4.2a)$$

The  $C_{PRE}^{DEF}$  computed from this binomial model will be substituted for  $B_{PRE}^{DEF}$  in multinomial logit model in (2a)

For Binomial Model 6, we have

$$\Pi_{CUR\_S}^{DEF}(t | X) = \frac{\exp(C_{CUR\_S}^{DEF}X)}{1 + \exp(C_{CUR\_S}^{DEF}X)} \quad (4.1b)$$

$$\Pi_{DEF}^{DEF}(t | X) = \frac{1}{1 + \exp(C_{CUR\_S}^{DEF}X)} \quad (4.2b)$$

The  $C_{CUR\_S}^{DEF}$  computed from this binomial model will be substituted for  $B_{CUR\_S}^{DEF}$  in multinomial logit model in (2b)

For Binomial Model 7, we have

$$\Pi_{CUR\_M}^{DEF}(t | X) = \frac{\exp(C_{CUR\_M}^{DEF}X)}{1 + \exp(C_{CUR\_M}^{DEF}X)} \quad (4.1c)$$

$$\Pi_{DEF}^{DEF}(t | X) = \frac{1}{1 + \exp(C_{CUR\_M}^{DEF}X)} \quad (4.2c)$$

The  $C_{CUR\_M}^{DEF}$  computed from this binomial model will be substituted for  $B_{CUR\_M}^{DEF}$  in multinomial logit model in (2c)

For Binomial Model 8, we have

$$\Pi_{CLM}^{DEF}(t | X) = \frac{\exp(C_{CLM}^{DEF}X)}{1 + \exp(C_{CLM}^{DEF}X)} \quad (4.1d)$$

$$\Pi_{DEF}^{DEF}(t | X) = \frac{1}{1 + \exp(C_{CLM}^{DEF}X)} \quad (4.2d)$$

The  $C_{CLM}^{DEF}$  computed from this binomial model will be substituted for  $B_{DEF}^{DEF}$  in multinomial logit model in (2d)

This way the estimation of the binomial logit (BNL) probabilities in (3.1a)-(3.2d) and (4.1a)-(4.2d) produces estimates of parameters of each of the elements of set  $C$  that can be substituted directly into equations (1a)-(1d) and (2a)-(2d) to derive the corresponding multinomial logit (MNL) probabilities.

#### B1.4. Loan Transition and Event Data

We used loan-level data to construct quarterly loan event histories by combining mortgage origination information with contemporaneous values of time-dependent factors. In the process of creating quarterly event histories, each loan contributed an additional observed “transition” for every quarter from origination up to and including the period of mortgage termination, or until the last time of the historical data sample. The term “transition” is used here to refer to any situation

in which a loan remains active, and the loan status is observed at the start of the next quarter, or in which terminal claim or prepayment events are observed in the current quarter.

The FHA single-family data warehouse (SFDW) records each loan for which insurance was endorsed and includes additional data fields updating the timing of changes in the status of the loan. The historical data used in model estimation for this Actuarial Review are from an extract from FHA’s database as of 2025.

### B1.5. Data Samples

A full 100-percent sample of loan-level data from the FHA single-family data warehouse was extracted for the FY 2025 analysis. This produced a very large sample of approximately 42 million single-family loans originated between the first quarter of FY 1975 and the fourth quarter of FY 2025. While our analysis of economic net worth will ultimately focus on those loans originated since FY 1995 that continue as active MMI Fund exposures, we include data as far back as FY 1975 to support the process of linking FHA streamline refinance (SR) loans to information associated with the original fully underwritten mortgage to the same borrower. Model estimation is based on data samples from the more recent FY 1995 through FY 2025 cohorts comprising those that impact the current economic net worth of the MMI Fund. Approximately 31 million loans have been endorsed for insurance during those years. For estimation, these data were used to generate quarterly loan-level event histories extending to the age at which the loan would mature based on the original term of the loan product or the end of the historical sample period. Forecasting the future performance of loans still active at the end of FY 2025 extends an additional 30 years out to FY 2055.<sup>74</sup>

Estimation and forecasting were undertaken separately for each of the following six FHA mortgage product types:

|           |          |                                                              |
|-----------|----------|--------------------------------------------------------------|
| Product 1 | FRM30    | Fixed-rate 30-year fully underwritten purchase and refinance |
| Product 2 | FRM15    | Fixed-rate 15-year fully underwritten purchase and refinance |
| Product 3 | ARM      | Adjustable-rate fully underwritten purchase and refinance    |
| Product 4 | FRM30 SR | Fixed-rate 30-year streamlined refinance                     |
| Product 5 | FRM15 SR | Fixed-rate 15-year streamlined refinance                     |
| Product 6 | ARM SR   | Adjustable-rate streamlined refinance                        |

#### B1.5.1. Random Sampling for Estimation and Validation

<sup>74</sup> As noted above, the review does not consider cashflows past 2055 on extended term (“ET”) modifications where the term to maturity is extended to 40 years. Discussions on the impact of such extension are provided in Appendix D.4.

The following random sampling rates were applied to the panel data for each product to produce the data for estimation and validation:

|           |          |             |
|-----------|----------|-------------|
| Product 1 | FRM30    | 10 percent  |
| Product 2 | FRM15    | 100 percent |
| Product 3 | ARM      | 100 percent |
| Product 4 | FRM30_SR | 100 percent |
| Product 5 | FRM15_SR | 100 percent |
| Product 6 | ARM_SR   | 100 percent |

The samples for each product were then evenly split by case number into estimation samples (50%) and validation samples (50%) to ensure there are no overlapping loan records in estimation and validation panel data samples.

The above sampling rates were motivated by fully utilizing historical data to the extent feasible, while recognizing that incorporation of the full Product 1 population was not necessary to achieve sufficient classification accuracy as per AUC scores and cross-validation performance as discussed below.

Proportional sampling was utilized for Product 1 to ensure sample representation of loans using alternative credit scores in proportion to the population. In general, FHA loan data include significant numbers of loans across all product types to support random sampling. There are two main channels through which alternatives to random sampling affected prior year reviews: (1) the use of alternative sources of credit score data for FHA loans with missing credit scores (primarily before 2004); and (2) over-sampling of default events and under-sampling of more prevalent non-default events.

The use of alternative sources of credit score data from the 1990s and early 2000s from a study conducted by UNICON Corporation raised issues of bias that could result from over-sampling of defaulted loans. Further oversampling of these loans to increase the share of loans having usable credit scores further magnified the potential bias issue. However, research by Manski and Lerman (1977) and others indicates that the impact of stratified sampling bias in logit models is limited to estimates of the intercept terms. In a stratified sample it is possible to control stratification impacts on coefficient estimates by including an indicator (0/1 dummy) for these loans (i.e., an indicator for the source of credit score).

Regarding over-sampling of quarterly default versus non-default events we have not implemented that approach as we found that all samples contained sufficient representation of transition events to achieve acceptable AUC scores and cross-validation results.

### B1.5.2 Random Sampling for Forecasting

Smaller samples are applied when forecasting the larger product types due to the significant expansion of the state-space when tracking prior default and prior mod status and the durations of default episodes and duration of cures. At the forecasting stage sample size sufficiency is reduced as the parameters are estimated and fixed and the main concern becomes representative coverage and weighting of all loan types and explanatory variables. Having multiple duplicates of more-or-less identical loans does not improve the accuracy of the forecasted performance of those loans to the extent that additional data improves the estimation of model parameters. Forecasting samples are therefore developed using stratified samples designed to ensure representativeness by cohort, LTV, and FICO.

### B1.5.3. Sample Periods for Transition Model Estimation

We used loans originated from FY 1996 through FY 2025 to estimate the status transition models. This covers the loan cohorts for which complete data were available on new 90-day default episodes. Quarterly observations from FY 2006 FQ 2 and FY 2007 FQ 3 were excluded from the estimation of transition probabilities for loans in default status (D, DX\_S, DX\_M) due to data issues associated with changes in the default episode tracking system in FY 2006.

## B2. Explanatory Variables

Four main categories of explanatory variables were employed:

1. Fixed initial loan characteristics including mortgage product type, purpose of loan (home purchase or refinance), amortization term, origination year and quarter, original loan-to-value (LTV) ratio, original loan amount, original mortgage interest rate, mortgage rate spread to market at origination, and relative house price level by geographic location (MSA, state, Census division).
2. Fixed initial borrower characteristics including borrower credit score, source of downpayment assistance, and first-time buyer indicator.
3. Dynamic variables based entirely on loan information including mortgage age, duration of default, duration of cure, whether a loan has had a prior default episode, whether a loan has had a prior loan modification, season of the year, and scheduled amortization of the loan balance.
4. Dynamic variables are derived by combining loan information with external economic data including interest rates and house price indexes to compute refinance incentives, current LTV, the relative spread of the coupon rate to market, the slope of the yield curve, and changes in household unemployment rates. A dynamic model explaining mortgage

decisions incorporating house price, inflation, and interest rate risk can be found in Campbell and Cocco (2015).

In some cases, the two types of dynamic variables are combined, as in the case of adjustable-rate mortgage (ARM) loans where external data on changes in one-year Treasury yields are used to update the original coupon rates and payment amounts by standard FHA loan contract features. This in turn affects the amortization schedules of the loans.

Goodness-of-fit and statistical significance metrics included in Appendix H demonstrate that specifications for all 48 models sufficiently explain variation in transition behavior across products and default status, a conclusion supported by the validation testing reported in Appendix B.

## B2.1 Fixed Initial Loan Characteristics

### B2.1.1. Mortgage Product Types

As described above, separate statistical models were estimated for the following six FHA mortgage product types:

|           |          |                                                              |
|-----------|----------|--------------------------------------------------------------|
| Product 1 | FRM30    | Fixed-rate 30-year fully underwritten purchase and refinance |
| Product 2 | FRM15    | Fixed-rate 15-year fully underwritten purchase and refinance |
| Product 3 | ARM      | Adjustable-rate fully underwritten purchase and refinance    |
| Product 4 | FRM30_SR | Fixed-rate 30-year streamlined refinance                     |
| Product 5 | FRM15_SR | Fixed-rate 15-year streamlined refinance                     |
| Product 6 | ARM_SR   | Adjustable rate streamlined refinance                        |

### B2.1.2. Loan-to-Value Ratio at Origination

Initial loan-to-value (LTV) is recorded in FHA's data warehouse for fully underwritten mortgages and SR loans with required appraisals. If available, these values are used directly. For SR loans without required appraisals, we attempt to apply the original LTV from the original fully underwritten mortgage (FUWM) to the same borrower. The FUWM is identified through a complicated matching process.

### B2.1.3. Relative Loan Size

Relative loan size is computed as the size of a borrower's loan relative to the average loan for the same product within the same geographic location. Relative loan size is an indicator of a borrower's position in the local income and house price distributions and historically has been associated with higher FHA claim rates at both the lower and upper range of values.

#### B2.1.4. Relative House Price

The relative house price variable was computed by comparing the original purchase price of the house underlying a particular mortgage with the Census median house value in the same period and location. We used Census median house price data at the county and Metropolitan Statistical Area (MSA) level obtained from Moody's.

#### B2.1.5. Spread at Origination

Spread-at-origination (SATO) is the relative difference between the original coupon rate versus the average mortgage offer rate at the time of origination. It is an indicator of the relative credit qualifications of the individual borrower, as higher values of SATO are associated with higher lending rates to less credit-worthy borrowers. Alternatively, lower values of SATO may indicate the willingness and ability of a borrower to pay more at closing to obtain a lower rate, thereby reducing their monthly payment burden and improving their ability to make continued payments on the mortgage and avoid default.

#### B2.1.6. Property Type

The majority of mortgages in the FHA single-family portfolio are single-unit properties, but other owner-occupied property types are also eligible for financing, including 2-unit (duplex) properties and 1-4-unit rental properties. We include dummy variables to control for these two property types and differences in their loan performance relative to that for 1-unit properties. We also include an indicator of whether a property is a condominium unit.

#### B2.1.7. Judicial Foreclosure State Indicators

The duration of default and foreclosure is likely to be longer for loans originating in states providing borrowers with a right to judicial foreclosure proceedings. We include an indicator of judicial foreclosure taking value 1 for loans originated in judicial foreclosure states and 0 otherwise. We find that this variable has a negative impact on default-to-claim probabilities for all products except ARM SR, where it is omitted from the specification. This suggests borrowers are slower to transition from default to claim, as expected, in states providing for the longer judicial foreclosure process.

#### B2.1.8. Deficiency Judgment State Indicators

We expect that lenders having the option to seek personal deficiency judgments against borrowers following foreclosure will discourage borrowers from defaulting. Some states that allow deficiency judgments on consumer and business loans may prohibit them in the case of residential foreclosures on mortgages that were secured by residential properties. Signs on current-to-default and default-to-claim transitions are mostly, although not always, negative.



## B2.2. Fixed Initial Borrower Characteristics

### B2.2.1. First-Time Buyer

An indicator for first-time buyers is included to distinguish these buyers from more experienced and seasoned buyers. The FHA single-family was originally developed to support first-time buyers with lower downpayments. The program has evolved over the years to include a broader cross-section of borrowers, particularly during the mortgage crisis years of 2007-2010 as emergency provisions were implemented to expand the availability of FHA-insured loans following the implosion of the subprime market and withdrawal of several private mortgage insurance providers. Nevertheless, first-time buyers still comprised around 84 percent of new originations,

### B2.2.2. Source of Downpayment Assistance

As documented in the FY 2006 and FY 2007 Reviews, the FHA single-family program experienced a significant increase in the use of downpayment assistance from relatives, non-profit organizations, and government programs. Loans to borrowers utilizing downpayment assistance from non-profit organizations have been observed to generate significantly higher claim rates. Although this particular form of downpayment assistance is now prohibited, it is still necessary to control its impact on historical loan performance. Following the approach first applied in the FY 2006 Review, we have included a series of indicators to control the use of different types of downpayment assistance by FHA borrowers. Through the process of linking streamlined refinance loans with the original fully underwritten FHA mortgages to the same borrowers, we have developed a parallel indicator of downpayment assistance received on the prior fully underwritten mortgages to apply when estimating the transition models for streamlined refinance loans. Thus, a streamline refinance loan originated in FY 2010, FY 2011 and the next few years may be issued to a borrower that was a prior recipient of downpayment assistance, and the type of prior downpayment assistance is controlled for in the loan status transition estimates for these loans. For this reason, some of the negative impacts of the earlier loans may carry over and impact the economic net worth of outstanding streamline refinance loans.

### B2.2.3. Borrower Credit Scores

Our primary source of credit scores on FHA single-family mortgages is those collected by FHA since 2004 and available from the SFDW. We supplement these data with additional credit score information collected through internal studies conducted for HUD that retrospectively obtained scores for FHA loan applications. The studies were conducted by UNICON Corporation and Fannie Mae. The UNICON study included credit scores collected for a sample of FHA applications from FY 1992, FY 1994, and FY 1996, and subsequently extended to loan applications during FY 1997 through FY 2004. This set of credit score data is useful because these loans have existed for many years and provide valuable historical delinquency, claim, and prepayment performance information. The Fannie Mae data provides additional credit score coverage for the

loans originated from FY 2000 to FY 2004. There is surprisingly little overlap between the two sources resulting in substantial credit score coverage during these years. Together the two data sources provide credit score information on hundreds of thousands of loans during a period in which none was collected by FHA. There are some limitations to the data. First, the data does not provide credit score data on all FHA loans originated during those years, so missing data remains an issue. Second, the data were initially collected for policy research purposes and were not randomly selected from all FHA loan applications. For example, there was an over-sampling of early-default loans among applications from FY 1997 through FY 2004. As a standalone dataset these loans are a stratified sample. This does not translate directly to our analysis as our loan samples are randomly selected based on all endorsed FHA loans. However, use of the data does imply that scores are not assigned to all FHA loans, and those that are assigned are not randomly selected. We address these issues by controlling the source of credit score data among our three sources (FHA, UNICON, Fannie Mae) and whether credit score remains missing as discussed under Section B1.5.1. Random Sampling for Estimation and Validation. These three sets of FICO data represent the most reliable sources of borrower credit history information available for historical FHA-endorsed loans before FY 2005 when FHA credit scores became available for almost all loans.

Through the process of linking streamlined refinance loans to the original fully underwritten FHA mortgages to the same borrowers we developed a parallel set of FICO score indicators for streamlined refinance loans and included these as explanatory variables when estimating the transition probability models for these products.

#### B2.2.4 Debt-to-Income (DTI) Ratio

The ratio of mortgage debt to income is a standard underwriting measure (front-end ratio) of borrower credit capacity and ability that is reported for individual borrowers in the SFDW. DTI ratio is a static measure collected during the loan application process.

### B3. Dynamic Variables Based on Loan Information

#### B3.1 Mortgage Age

Mortgage age is an important predictor of mortgage performance. Conditional default, cure, claim, and prepayment rates tend to be non-linear over age even when many other factors are controlled statistically.<sup>75</sup> A flexible and efficient way to represent these non-linearities is through the application of piece-wise linear spline functions. These represent the age function as a sequence of linear segments with different slopes but connecting exactly at a sequence of specified age values. This concept is illustrated for a 6-segment age function in Exhibit B-3.

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<sup>75</sup> Except for age, there are several other loan characteristics and borrower behaviors presenting non-linear influence on mortgage status transitions (Sadhvani, Giesecke, and Sirignano, 2021). We apply the same piece-wise linear spline method wherever appropriate.

### Exhibit B-3: Example of a 6-Segment Mortgage Age Functions

$$\text{age1} = \begin{cases} \text{AGE} & \text{if AGE} \leq k_1 \\ k_1 & \text{if AGE} > k_1 \end{cases}$$

$$\text{age2} = \begin{cases} 0 & \text{if AGE} \leq k_1 \\ \text{AGE} - k_1 & \text{if } k_1 < \text{AGE} \leq k_2 \\ k_2 - k_1 & \text{if AGE} > k_2 \end{cases}$$

$$\text{age3} = \begin{cases} 0 & \text{if AGE} \leq k_2 \\ \text{AGE} - k_2 & \text{if } k_2 < \text{AGE} \leq k_3 \\ k_3 - k_2 & \text{if AGE} > k_3 \end{cases}$$

$$\text{age4} = \begin{cases} 0 & \text{if AGE} \leq k_3 \\ \text{AGE} - k_3 & \text{if } k_3 < \text{AGE} \leq k_4 \\ k_4 - k_3 & \text{if AGE} > k_4 \end{cases}$$

$$\text{age5} = \begin{cases} 0 & \text{if AGE} \leq k_4 \\ \text{AGE} - k_4 & \text{if } k_4 < \text{AGE} \leq k_5 \\ k_5 - k_4 & \text{if AGE} > k_5 \end{cases}$$

$$\text{age6} = \begin{cases} 0 & \text{if AGE} \leq k_5 \\ \text{AGE} - k_5 & \text{if AGE} > k_5 \end{cases}$$

Coefficient estimates corresponding to the slopes of the line segments between each knot point and for the slope of the last line segment were estimated for each product and transition type combination. The resulting overall AGE function for the 6-age segment example described above is given by:

$$\text{Age Function} = \beta_1 \cdot \text{age1} + \beta_2 \cdot \text{age2} + \beta_3 \cdot \text{age3} + \beta_4 \cdot \text{age4} + \beta_5 \cdot \text{age5} + \beta_6 \cdot \text{age6}$$

Age functions with fewer or greater numbers of segments are developed similarly. The number of segments and the selection of the knot points were determined by testing alternative specifications and assessing the reasonableness of the resulting functions. For some products and transition types, age functions were reduced to simple linear functions or were omitted altogether due to the instability or statistical non-significance of the estimated parameters. For example, mod-cure and self-cure transition probabilities are not as closely related to mortgage age as other events, such as current-to-default or current-to-prepayment transitions.

#### B3.2. Prior Loan Default Indicator

A loan that experiences a 90-day default episode and later returns to the current status is then classified as having had a prior default episode. Once this occurs and the dummy (0/1) variable

for prior default is set to 1, it remains at this value for the remainder of the loan life. This enables us to distinguish these loans from those that have never entered the 90-day default status, a strong predictor of subsequent default, and a negative factor for the likelihood of prepayment.

### B3.3. Prior Loan Modification Indicator

Loan modifications are identified from the default episodes data and once the modified loan has returned to current status (cured) it is categorized as having had a prior loan modification. Once this occurs and the dummy (0/1) for the prior loan mod is set to 1, it remains at this value for the remainder of the loan life.

### B3.4. Duration of Default Episode

The duration of a default episode is 0 at the start of the first full quarter following the date of entry into 90-day default status and then increments by one for each additional quarter spent in default status. For model estimation, the number of quarters in default is entered as a series of dummy variables for values from 0 to 5, where 5 represents 5 or more quarters. This variable applies only to variables in default status and is reset to zero at the start of any new default episode.

### B3.5. Duration of Cure Episode

Each time a defaulted loan returns to status, we track the number of quarters since the default episode ended. The values include 0 at the initial return to current and then increments by 1 quarter as long as the loan remains current. For model estimation, the number of quarters current is entered as a series of dummy variables for values from 0 to 5, where 5 represents 5 or more quarters. This variable only applies to current loans with a prior default and current loans with no prior default are assigned 0 values for this variable.

### B3.6. Seasonality Indicator

The season of an event observation quarter is defined as the season of the year corresponding to the calendar quarter identified as Winter (January, February, March), Spring (April, May, June), Summer (July, August, September), and Fall (October, November, December). Historically borrowers are least likely to default or have a non-SR prepayment during the Winter months. Not surprisingly, prepayments to SR follow a less consistent pattern as these are undertaken primarily in response to favorable interest rate conditions and exclude prepayments for purposes of residential mobility.

### B3.7. Time-Period Indicators for Policy Changes

Loss Mitigation FY 2021 FQ3 to FY 2025 FQ4 – Period of extended COVID loss mitigation procedures extended through and expire on September 30, 2025, per Mortgagee Letter 2025-12. This variable captures the prolonged impact of loss mitigation policy changes in response to COVID pandemics on loan status transitions and associated loss mitigation costs. We control

these effects for the forecasting period, following the implementation of the new loss mitigation waterfall effective October 1, 2025.

## B4. Dynamic Variables Incorporating External Economic Data

### B4.1. FHFA House Price Indices

Consistent with the PEA, historical house price indices (HPIs) produced and published by FHFA were applied in loan status transition model estimation. We opt for broader geographic coverage at the MSA level. The HPI PO version is applied at the state level when no MSA-level HPI is available, and the national level is applied if the state level is not available.

### B4.2. Current Loan-to-Value (CLTV) Ratio

The current loan-to-value (CLTV) is computed as the ratio of the current property value to the outstanding loan balance. Current property values are derived by updating the original purchase price or appraised value of the collateral property using local-area house price indices (HPIs) from FHFA. Metro-level HPIs are used if available, otherwise, a state-level HPI is applied. This is a dynamic variable that is updated based on changes in the HPI and amortization of the loan balance. For SR loans with no appraisals with identified original FUWMs, we utilize the original property value and loan balance of the FUWM to derive the current LTV.

### B4.3. House Price Volatility

House price volatility parameter estimates are a byproduct of the estimation of the FHFA weighted-repeat-sales HPIs. FHFA publishes the estimated volatility parameters at state-level and has provided FHA with MSA-level volatility parameter estimates for application to the FY 2025 review. The volatility parameters can be used to derive the expected dispersion of individual house price appreciation around the market average represented by HPI. Higher dispersion makes it more likely that an individual housing value may be too low to enable a borrower to qualify for refinancing. This will reduce the probability of prepayment and increase the probability of default for borrowers subject to higher and higher levels of volatility. Since the dispersion of individual housing values increases over time, so does the probability of negative equity. While these estimates are developed over time as parameters of the house price diffusion process, we apply them as cross-sectional indicators of relative market volatility in the borrower's location.

### B4.4. House Price Appreciation

The FHFA HPIs are used to compute short-term rates of local and national house price appreciation as proxies for borrower expectations regarding future house price changes. These measures provide alternative indicators of market conditions that may impact the likelihood of prepayment, default, or cure in different directions. For example, borrowers whose personal or loan factors may increase their chances of default may have greater opportunities to sell their property and avoid default through prepayment if local markets are appreciating. Conversely, borrowers in

declining markets may be less mobile in the face of strong national appreciation, thus reducing the likelihood of prepayment and increasing the risk of default. The local house and national house price appreciation (HPA) measures are computed as the ratio of the region-specific HPI one-year ahead to the value of the same HPI one-year prior:

$$HPA = \frac{HPI(t+1)}{HPI(t)} - 1$$

#### B4.5. Refinance Incentive

The financial incentive of a borrower to refinance is measured using a variable for the relative spread between the current mortgage contract interest rate and the current market mortgage rate:

$$MP(t) = \left\{ \frac{C(t) - R(t)}{C(t)} \right\}$$

Where  $C(t)$  is the current note rate on the mortgage and  $R(t)$  is the current market average fixed-rate mortgage rate. This variable approximates the call option value of the mortgage given by the difference between the present value of the “anticipated” future stream of mortgage payments discounted at the current market rate of interest,  $R(t)$ , and the present value of the mortgage evaluated at the current note rate,  $C(t)$ . Additional details are given in Deng, Quigley, and Van Order (2000) and Calhoun and Deng (2002).

The relative mortgage premium values for ARMs and FRMs are derived in the same manner, except that the current coupon is always equal to the coupon at origination for FRMs, whereas ARM coupon rates are updated over the life of the mortgage as described next.

#### B4.6. Unemployment Rate Change

Unemployment impacts are captured by including changes in household unemployment rates at the metropolitan area level, or at the state level for non-metro area loans. Unemployment rates are a stock variable showing the size of the pool of unemployed during a point in time. By looking at changes in unemployment rates we can better capture the likelihood that a borrower is at greater or lesser risk of entering unemployment. The unemployment rate change is computed as the difference between the rates observed one period prior and three-periods prior:

$$delta\_ue = ue\_rate(t-1) - ue\_rate(t-3)$$

#### B4.7. Refinance Burnout

Refinance burnout is the tendency for borrowers who have missed refinance opportunities in the past to have lower conditional probabilities of prepayment going forward. A burnout factor is included to identify borrowers who have foregone recent opportunities to refinance. The burnout factor is quantified as the moving average number of basis points the borrower was in the money, for all quarters during which the borrower was in the money, during the preceding 8 quarters. The



refinance burnout factor is included to account for individual differences in propensity to prepay, often characterized as unobserved heterogeneity. Empirical evidence now suggests that borrowers who refinance now tend to do so at much lower thresholds than in the past.

#### B4.8. Credit Burnout

Credit burnout exists when borrowers with negative equity do not default as expected and then have lower-than-average default rates going forward. As with refinance burnout this may be interpreted as the impact of unobserved heterogeneity among borrowers but may also be attributed to unmeasured differences in borrower equity at the loan level. Credit burnout is quantified as the cumulative number of quarters the loan has been in a negative equity position as indicated by values of current LTV greater than 100 percent.

#### B4.9. ARM Coupon Rate Dynamics

To estimate the current financial value of the prepayment option for ARM loans, and to compute amortization rates that vary over time, we needed to track the path of the coupon rate over the active life of individual ARM loans. The coupon rate resets periodically to a new level that depends on the underlying index, plus a fixed margin, subject to periodic and lifetime caps and floors that specify the maximum and minimum amounts by which the coupon can change on each adjustment date and over the life of the loan. Accordingly, the ARM coupon rate at time  $t$ ,  $C(t)$ , was computed as follows:

$$C(t) = \max \{ \min [ \text{Index}(t - S) + \text{Margin}, \\ C(t - 1) + A(t) \cdot \text{Period\_UpCap}, C(0) + \text{Life\_UpCap}], \\ C(t - 1) - A(t) \cdot \text{Period\_DownCap}(t), \max (C(0) - \text{Life\_DownCap}, \text{Life\_Min}) \}$$

where  $\text{Index}(t)$  is the underlying rate index value at time  $t$ ,  $S$  is the “look back” period, and  $\text{Margin}$  is the amount added to  $\text{Index}(t - S)$  obtain the “fully indexed” coupon rate. The periodic adjustment caps are given by  $\text{Period\_UpCap}$  and  $\text{Period\_DownCap}$ , and are multiplied by a dummy variable  $A(t)$  which equals zero except during scheduled adjustment periods. Maximum lifetime adjustments are determined by  $\text{Life\_UpCap}$  and  $\text{Life\_DownCap}$ , and  $\text{Life\_Min}$  is the overall minimum lifetime rate level. Any initial discounts in ARM coupon rates are reflected in the original interest rate represented by  $C(0)$  in equation (12).

#### B4.10. ARM Payment Shock

The relative change in the monthly payment on ARM loans since origination is an approximation to the call option value of prepayment. We calculate this as follows:

$$\text{arm\_pmt\_shock}(t) = 100 \times \frac{PMT(t) - PMT(0)}{PMT(0)}$$



The ARM payment shock measure is expected to have a positive impact on current-to-prepay, current-to-default, and default-to-claim transitions for non-SR ARM loans since it represents both the value of the prepayment option and is a direct measure of the payment burden of ARM loans if interest rates increase significantly after origination, although these impacts will be delayed and negated somewhat given the annual and lifetime caps on ARM coupon rate increases.

#### B4.11. Yield Curve Slope

Expectations about future interest rates and differences in short-term and long-term borrowing rates associated with the slope of the Treasury yield curve influence the choice between ARM and FRM loans and the timing of refinancing. We use the ratio of the ten-year Constant Maturity Treasury (CMT) yield to the one-year CMT yield to measure the slope of the Treasury yield curve.

#### B4.12. Current Exposure-Period FRM Offer Rate

A variable measuring the market average FRM mortgage rate during each period is included to distinguish particularly high-rate or low-rate market environments.

### B5. Prior Loan Information for Streamline Refinance Mortgages

We apply a method first developed in the FY 2010 Review that links streamlined refinance mortgages to the original fully underwritten FHA loans previously issued to the same borrower. Many FHA borrowers received multiple streamlined refinances over time, so the process of linking any given streamlined refinance mortgage to their original ancestor loan often requires establishing prior linkages through a sequence of FHA SR loans. We can identify the original fully underwritten FHA mortgage (FUWM) for about 95 percent of all streamlined refinance mortgages endorsed for FHA insurance since FY 1993.

Here we provide a brief explanation of the SR matching process. Each SR loan record includes a current FHA case number (`case_nbr`) and a prior FHA case number for the preceding FHA loan to the same borrower (`old_case_nbr`). If we assign the `old_case_nbr` of the subject SR loan to a new variable, call it `match_case_nbr`, and then assign the actual case numbers of all other loans to the same variable, we can sort by date and `match_case_nbr` any matching loans should appear together in chronological order in the data. This requires matching the SR with `old_case_nbr = match_case_nbr` against all loans for all product types within a state since the subject SR may have streamlined refinanced from any one of the 6 product types. Matching within a state is sufficient since the borrower and the property location must be the same for all potential matches.

Once the first match is obtained, we create a new combined match group/match sequence code to uniquely identify matched loans. We can then repeat the entire process for the newly matched prior SR loan using its `old_case_nbr`. Some borrowers undertake more than a dozen SRs, so we repeat the process again and again until we match with the original FUWM. Along the way, we create a two-digit refi-type sequence number that identifies the two product types involved in each match. This also enables us to later distinguish SR from non-SR prepayment terminations for the

last SR in the sequence. If the sorting-matching process fails to identify the original FUWM, we attempt a direct match of `old_case_nbr` for any unmatched SR loan to the `case_nbr` values of unmatched non-SR loans to obtain a few additional matches. The entire process yields match rates in the range of 92 to 98 percent of SR loans depending on the vintages and state locations of the SR loan.

The main benefit of linking SR mortgages with the original FUWM is that it enables us to use underwriting characteristics and other information from that original FUWM in predicting the behavior of later SR loans to the same borrowers. For example, the process of updating current LTVs usually begins at loan origination and proceeds period-by-period over the life of the loan. In the case of the streamline refinance mortgage, we can obtain the original LTV and property values of the FUWM and update from that point forward, as if the current streamline refinance was a continuation of the original mortgage (for this purpose only, not for amortization and other dynamic processes specific to the current loan). We only apply this process to streamline refinance mortgages without required appraisals. In those cases where appraisals were required, we used the information from that appraisal to compute the current LTV for the streamline mortgage. We are also able to assign indicators of original LTV, relative house price, and downpayment assistance type to current streamline mortgages based on the original fully underwritten mortgage and to include these variables in the models for streamlined mortgage products. Finally, we develop indicators of the prior product type to include as an additional explanatory variable in the status transition models for SR loans.

## B6. Transition Model Validation and Backtesting

Model validation is required to comply with Actuarial Standards of Practice 23 (Data Quality) and 56 (Modeling). ASOP 23 applies when an actuary is selecting, using, or relying on data provided by others, all of which are relevant to our review of MMI Fund performance. ASOP 56 provides guidance on designing, developing, selecting, modifying, and using models when performing actuarial services. We employ models that are descended from those originally developed by members of our team and applied in the 2004 to 2016 actuarial reviews. As such, the models we use are the culmination of a multi-year process of model design, development, and application that we feel contributes meaningfully to the current validation process. This ongoing process has also provided us with considerable past experience with the data required for estimation and forecasting the performance of FHA single-family mortgages. Nevertheless, we are not simply relying on prior models and past experience. We have undertaken an expansive and fresh look at data and model development to support the FY 2025 review.

The primary data source for our analysis is the FHA Single-Family Data Warehouse (SFDW). We consider that the SFDW is compliant with ASOP 23 regarding the appropriateness, availability of current information, internal consistency of the data, and comprehensive coverage of current and past FHA mortgages. The data are well documented by the SFDW Meta Data workbook that ITDC requested from HUD to better understand the available data. The SFDW is an appropriate and

sufficient source of FHA loan data, including detailed information on over 60 million single-family mortgages.

ASOP 23 instructs us to consider known data limitations. Historically, data limitations specifically impacting loan performance model development efforts include: (1) missing borrower credit scores; (2) missing detail on default episodes; and (3) missing underwriting information on FHA streamline refinance (SR) originations. The first two issues have faded as concerns over time as FHA improved its credit scoring and default tracking systems. Nevertheless, we still rely on mortgage data for loans originated as many as 30 years ago, so that these issues must still be addressed in modeling.

The first issue of missing credit score information has been addressed in our modeling using additional data from HUD research studies that provides credit score information prior to 2004 when FHA began collecting credit score information on every loan. The second issue of default episode tracking has been addressed at HUD with three major improvements to default data collection in 1990, 1996, and 2006, such that each 90-day default episode is now tracked. The third issue regarding limited or missing underwriting data for SRs is simply a feature of these loans that makes them attractive to existing FHA borrowers. We have developed a partial solution to the problem through a process of matching SR loans back to the original full-underwritten loan to the same FHA borrowers. That process is complicated by the fact that some borrowers undertake more than 10 successive streamline refinance originations. The matching process provides the benefit of adding some information on the original fully underwritten FHA mortgage that can be used in modeling the performance of the latest SR mortgage, such as their original LTV and property value, which can be used to extrapolate forward to obtain an estimate of the LTV at origination of the latest SR loan.

To avoid data attrition missing values for LTV, current LTV, DTI, and credit score, we retain as many observations as possible by treating missing values as a categorical factor (reference group) in the variables.<sup>76</sup>

The primary ASOP 56 requirement for model output validation is that the model output reasonably represents that which is being modeled, which in our case are loan status transition probabilities and loan insurance cash flows.<sup>77</sup> The validation should include testing the model output against observed historical results and evaluating whether the model output applied to hold-out data is reasonably consistent with model output developed without using the hold-out data. ASOP 56 also raises the issue of potential model over-fitting, defined as a situation where the model fits the data used to develop the model so closely that prediction accuracy materially decreases when the model is applied to different data. For example, over-fitting may occur when an excessively flexible function form is applied to a relatively small number of data points, such that the model explains those data almost perfectly, while failing to conform to other data from the same process.

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<sup>76</sup> The proportions of missing values for these variables are too large to perform any meaningful value imputation.

<sup>77</sup> Cash flow model backtesting and validation are discussed in Appendix D.

The voluminous data available from the SFDW mitigates the risk of over-fitting, even for models with large numbers of explanatory variables.

The below table shows the AUC for each transition model, both for the estimation dataset and a holdout sample:

Exhibit B-4: AUC, Transition Model Estimation Holdout Samples

| Product | Transition         | Estimation AUC | Validation AUC |
|---------|--------------------|----------------|----------------|
| 1       | current_default    | 0.7881         | 0.7871         |
| 1       | current_currentX   | 0.8445         | 0.8450         |
| 1       | current_prepay_nsr | 0.7577         | 0.7582         |
| 1       | current_prepay_sr  | 0.8805         | 0.8801         |
| 1       | default_claim      | 0.7405         | 0.7402         |
| 1       | default_prepay     | 0.7802         | 0.7806         |
| 1       | default_cure_s     | 0.7551         | 0.7542         |
| 1       | default_cure_m     | 0.7802         | 0.7816         |
| 2       | current_default    | 0.8344         | 0.8345         |
| 2       | current_currentX   | 0.8717         | 0.8744         |
| 2       | current_prepay_nsr | 0.6565         | 0.6572         |
| 2       | current_prepay_sr  | 0.8849         | 0.8853         |
| 2       | default_claim      | 0.7620         | 0.7646         |
| 2       | default_prepay     | 0.7343         | 0.7353         |
| 2       | default_cure_s     | 0.8098         | 0.8063         |
| 2       | default_cure_m     | 0.8166         | 0.8155         |
| 3       | current_default    | 0.7756         | 0.7751         |
| 3       | current_currentX   | 0.8205         | 0.8144         |
| 3       | current_prepay_nsr | 0.7515         | 0.7512         |
| 3       | current_prepay_sr  | 0.8105         | 0.8103         |
| 3       | default_claim      | 0.7357         | 0.7336         |
| 3       | default_prepay     | 0.7663         | 0.7651         |
| 3       | default_cure_s     | 0.7777         | 0.7781         |
| 3       | default_cure_m     | 0.7734         | 0.7754         |
| 4       | current_default    | 0.7924         | 0.7920         |
| 4       | current_currentX   | 0.8390         | 0.8392         |
| 4       | current_prepay_nsr | 0.7234         | 0.7228         |
| 4       | current_prepay_sr  | 0.8676         | 0.8671         |
| 4       | default_claim      | 0.6958         | 0.6966         |
| 4       | default_prepay     | 0.7779         | 0.7786         |
| 4       | default_cure_s     | 0.7620         | 0.7625         |
| 4       | default_cure_m     | 0.7770         | 0.7758         |
| 5       | current_default    | 0.7888         | 0.7896         |
| 5       | current_currentX   | 0.8307         | 0.8063         |
| 5       | current_prepay_nsr | 0.6661         | 0.6653         |
| 5       | current_prepay_sr  | 0.9038         | 0.9029         |

| Product | Transition         | Estimation AUC | Validation AUC |
|---------|--------------------|----------------|----------------|
| 5       | default_claim      | 0.7186         | 0.7095         |
| 5       | default_prepay     | 0.7042         | 0.7043         |
| 5       | default_cure_s     | 0.8405         | 0.8352         |
| 5       | default_cure_m     | 0.8230         | 0.8241         |
| 6       | current_default    | 0.7160         | 0.7188         |
| 6       | current_currentX   | 0.8087         | 0.8132         |
| 6       | current_prepay_nsr | 0.7330         | 0.7359         |
| 6       | current_prepay_sr  | 0.7965         | 0.7966         |
| 6       | default_claim      | 0.6798         | 0.6751         |
| 6       | default_prepay     | 0.7773         | 0.7779         |
| 6       | default_cure_s     | 0.7745         | 0.7680         |

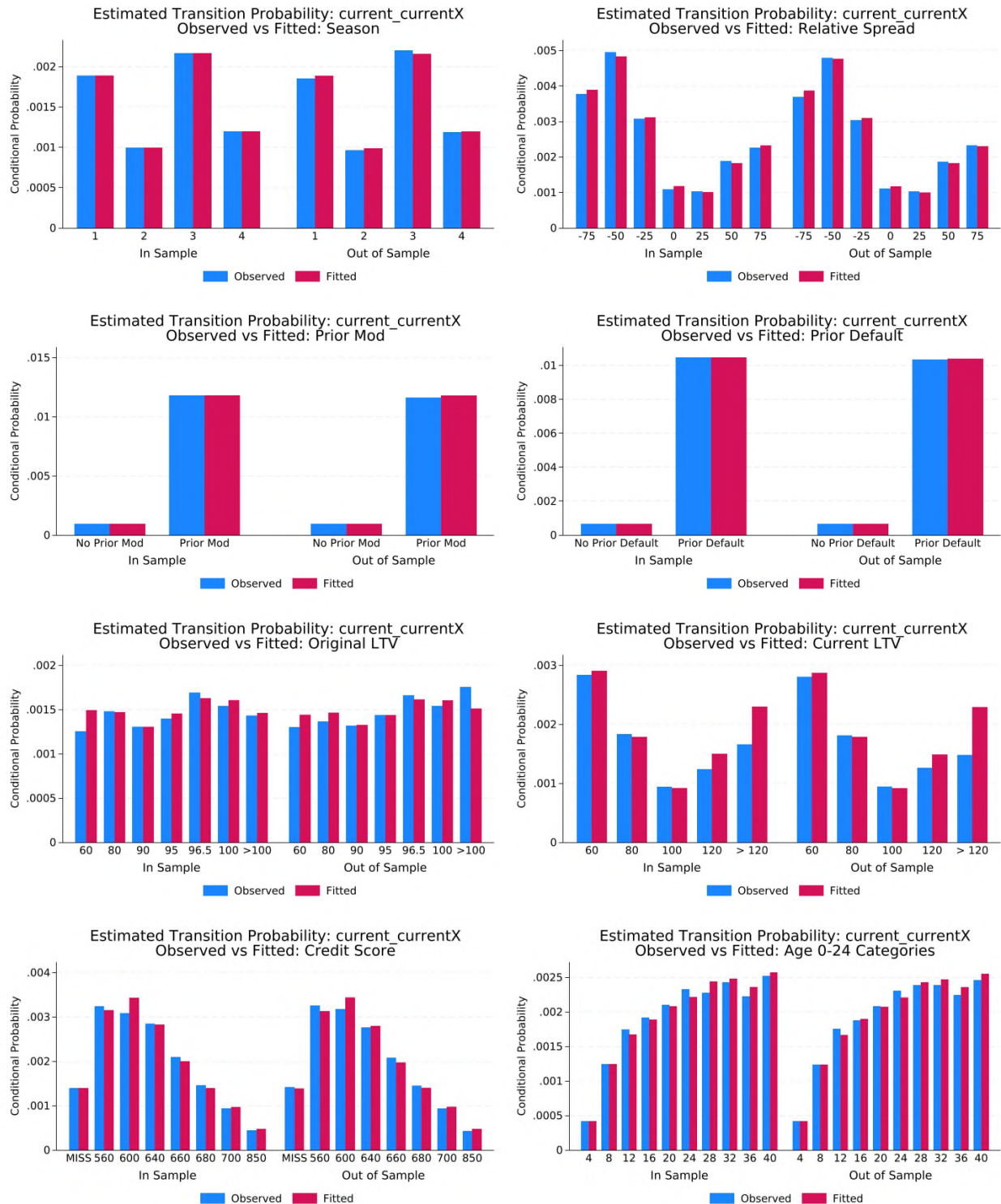
Relatedly, it may be asked whether our transition model outputs, which are estimated loan status transition probability functions, can reasonably represent observed average loan status transition frequencies. We will demonstrate this using a series of comparisons based on whether fitted loan status transition probabilities estimated using one sample are accurate in predicting observed loan status transition rates in a hold-out sample from the same data, but where the latter were not used in estimation.

We include the results of our comparisons for each loan status transition type comprising the dependent variables in our logit estimation models. We compared fitted and observed transition rates stratified across explanatory factors similar to those used in our transition models, including: original LTV, credit score, current LTV, relative spread (refinance incentive), mortgage age, season of year, prior default, prior mod, duration of cure for loans initially in current status, and duration of default for loans initially in default status.

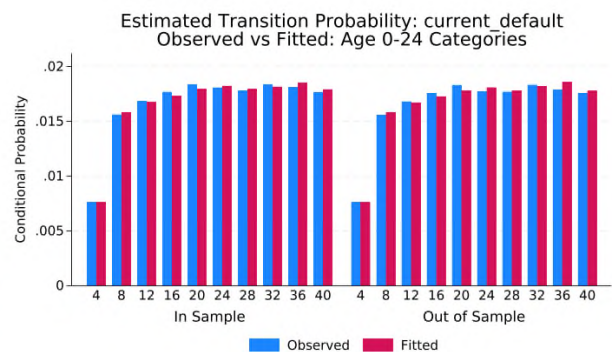
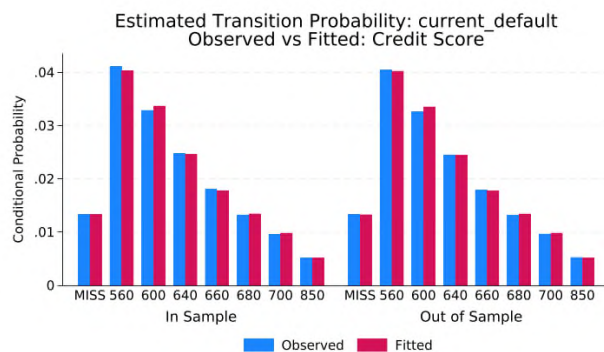
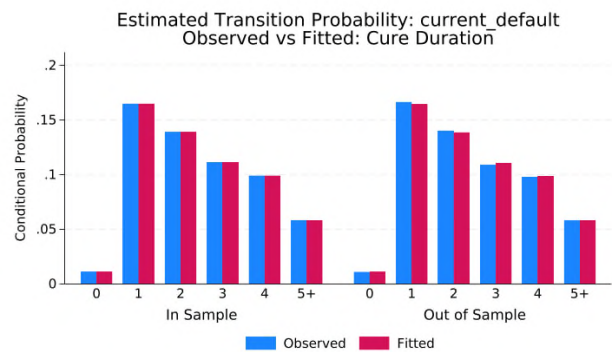
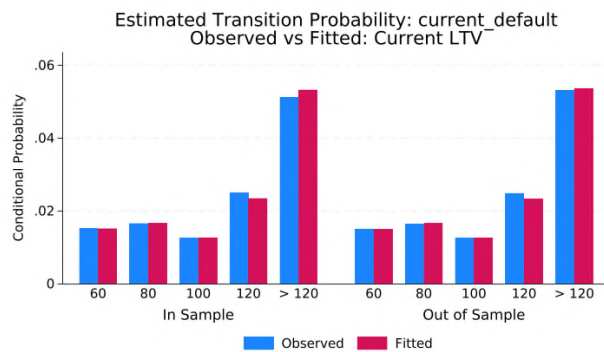
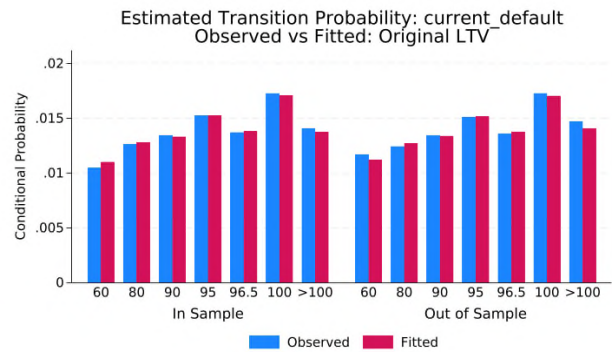
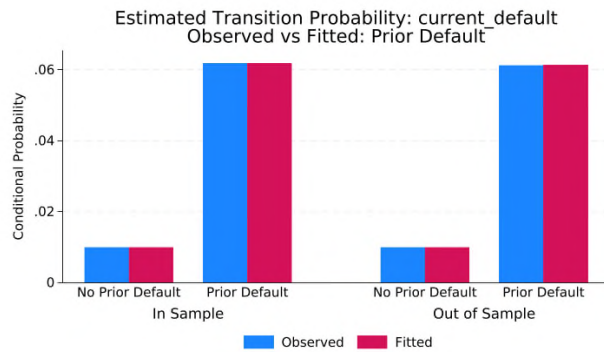
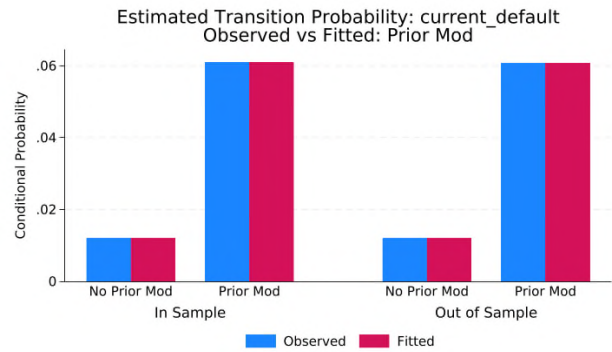
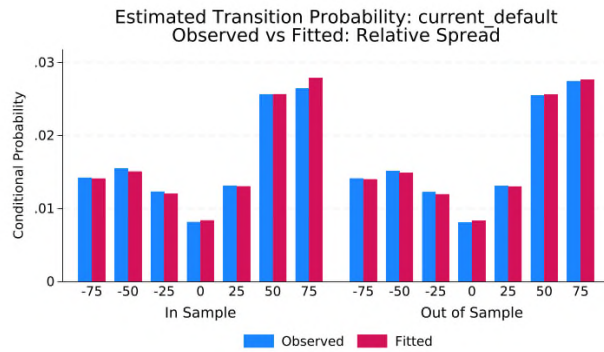
The model fits indicated by these comparisons appear quite good, with little deviation of the average fitted rates from the average observed rates of transition in most comparisons, confirming the effectiveness of transition model regression specifications, and that model outputs reasonably represent what was being modeled as required by ASOP 56.



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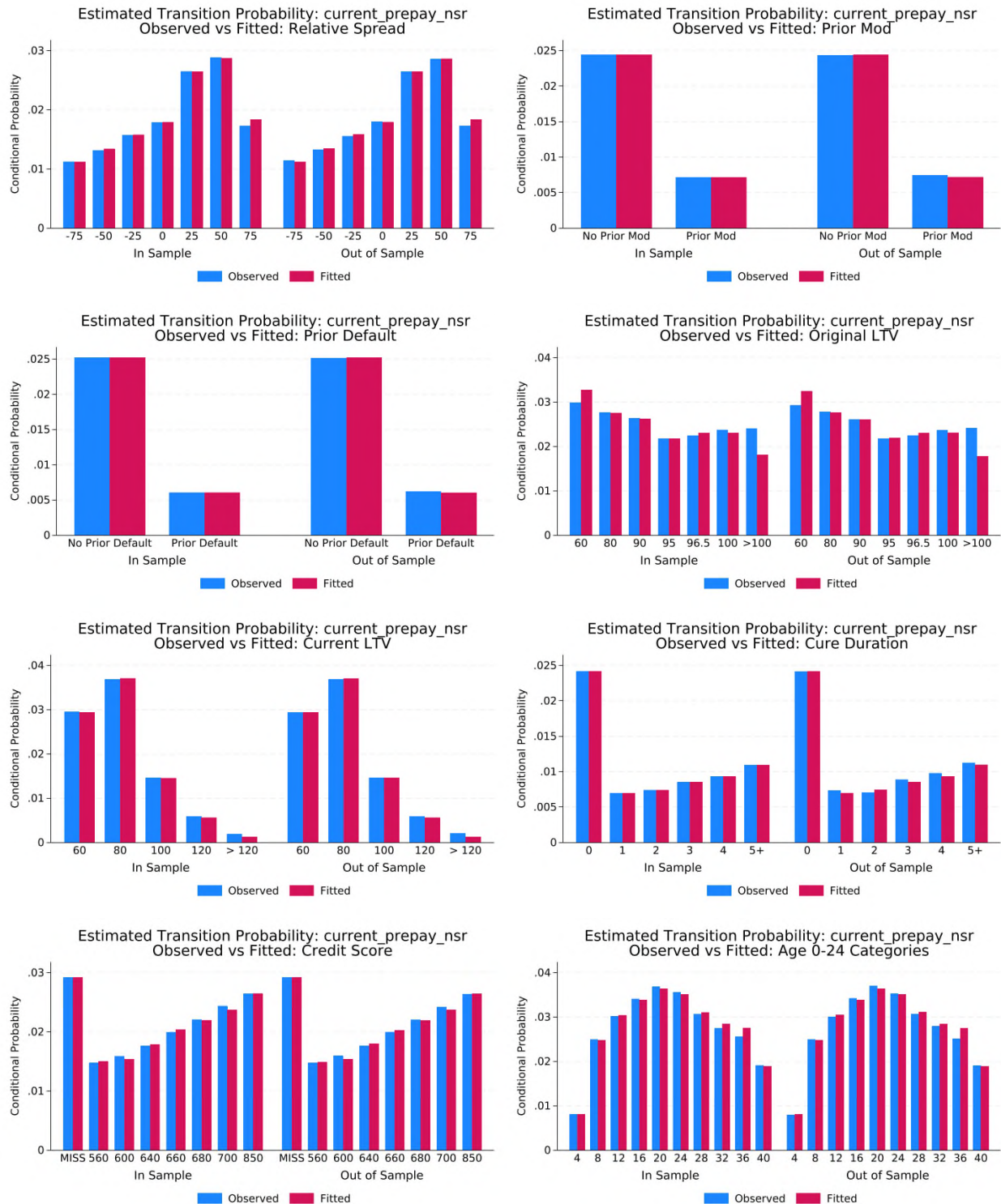


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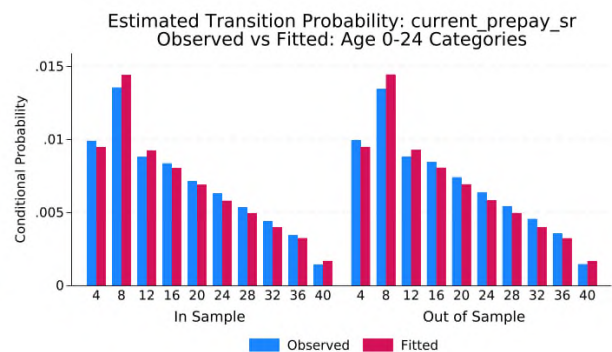
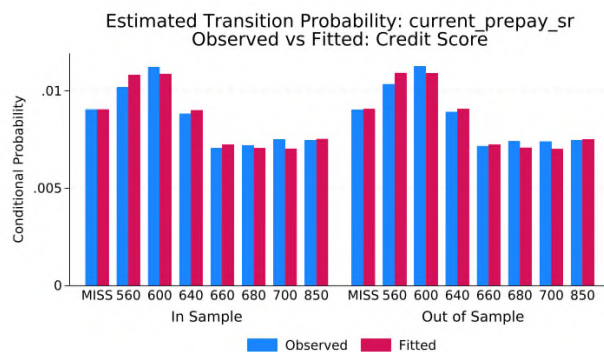
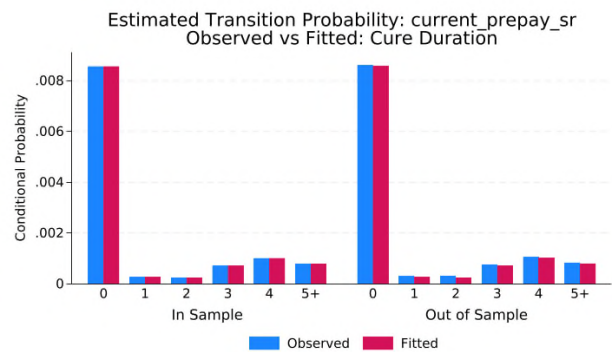
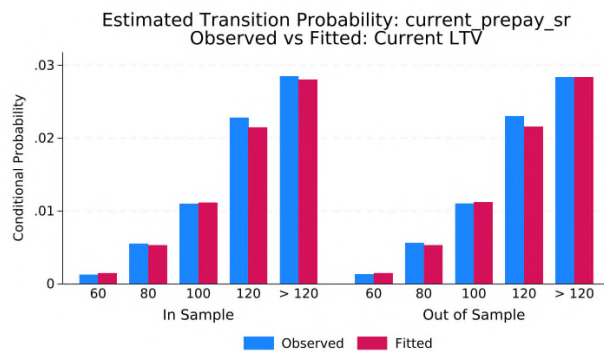
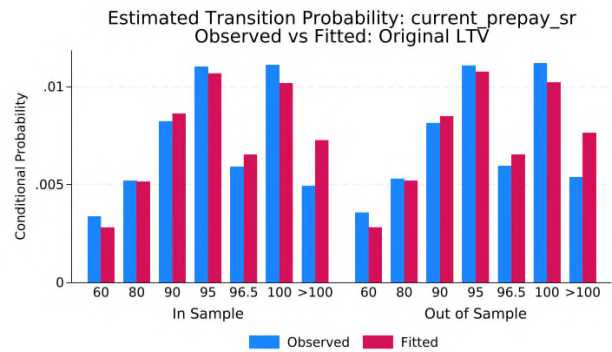
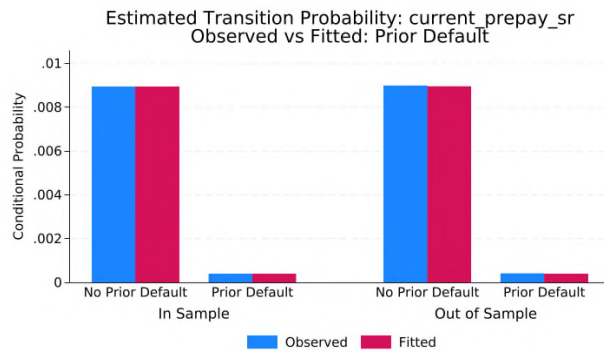
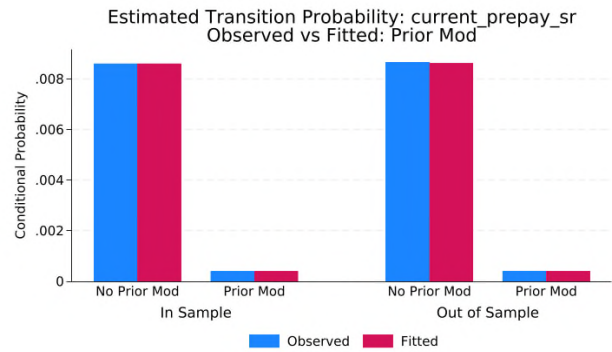
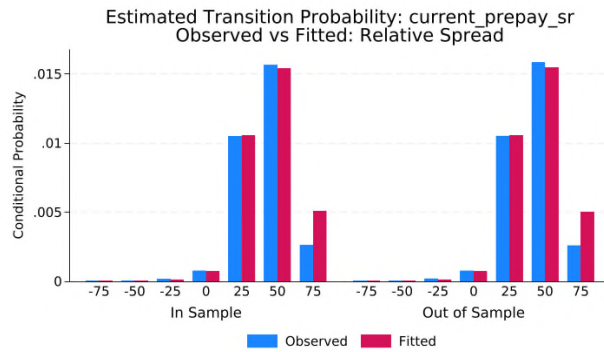




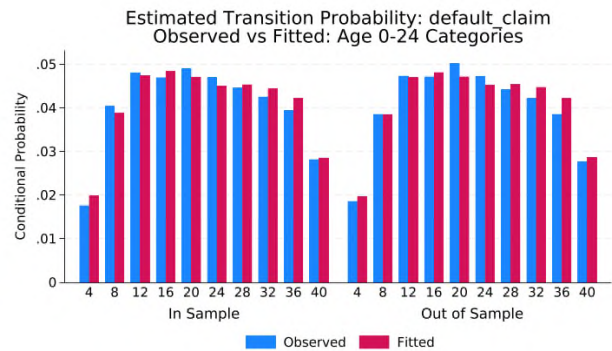
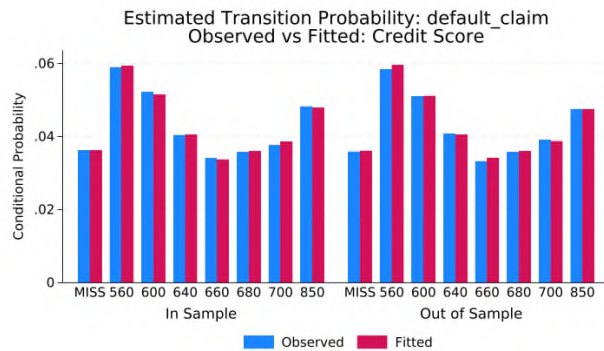
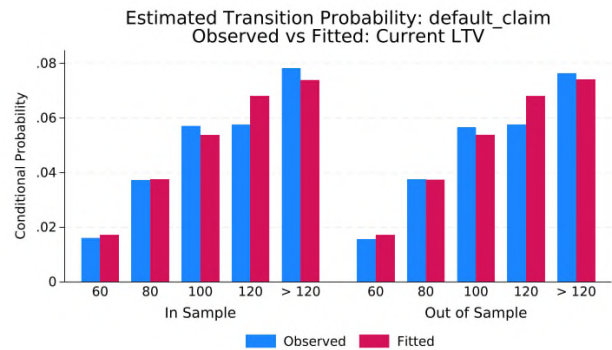
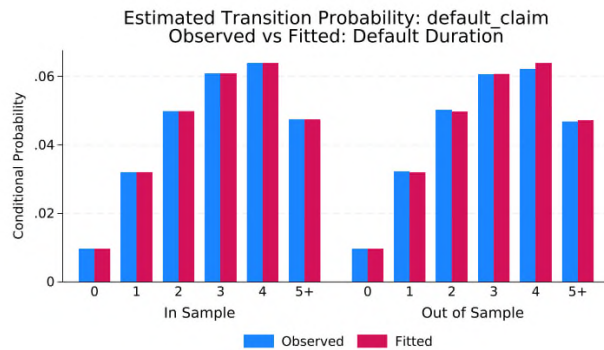
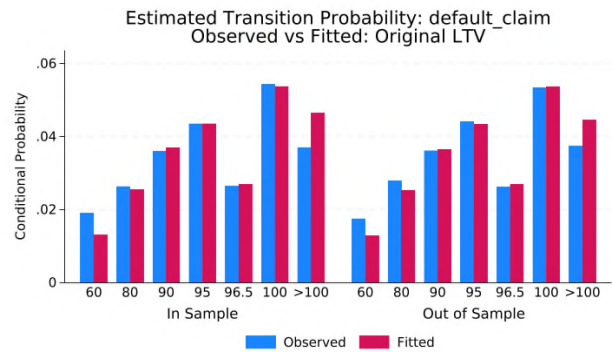
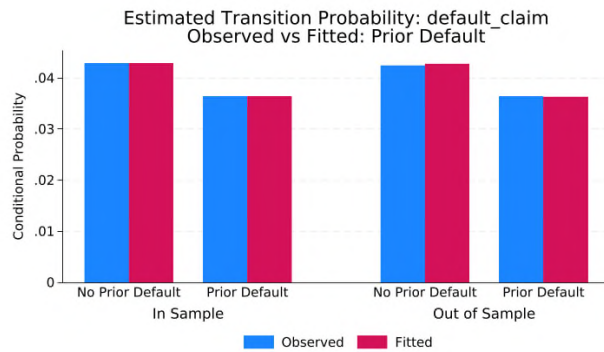
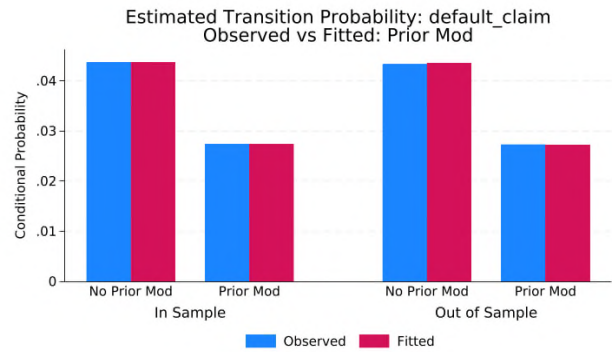
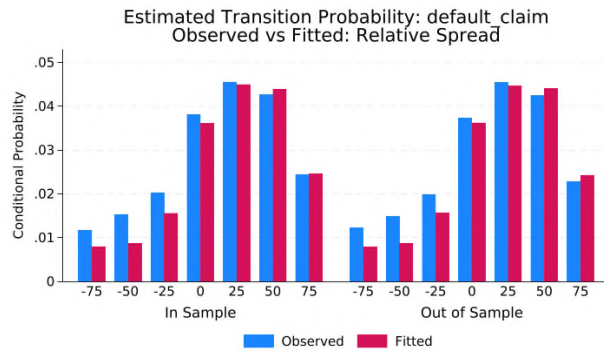
## Product 1 - current\_prepay\_nsr



## Product 1 - current\_prepay\_sr

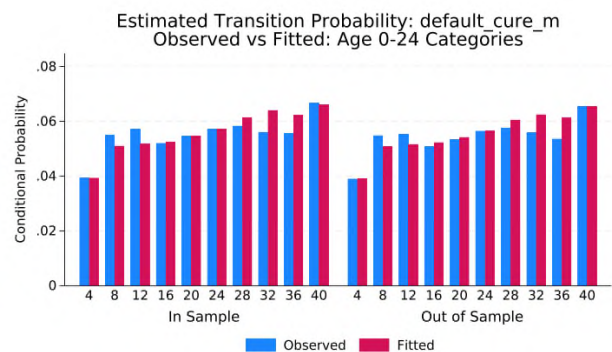
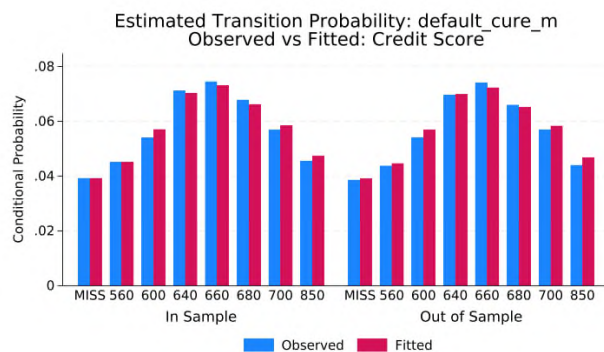
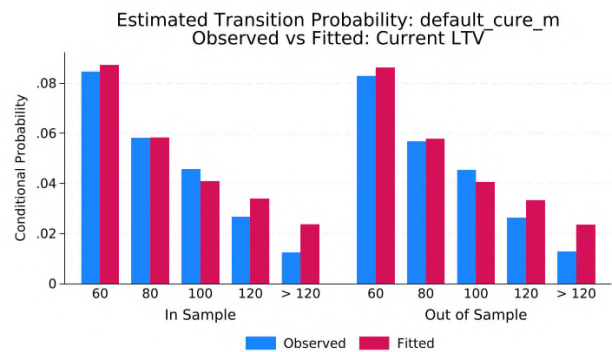
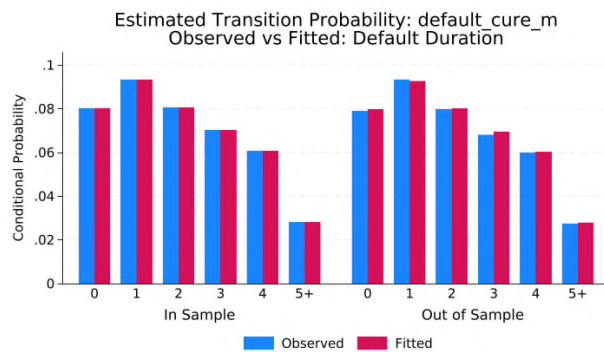
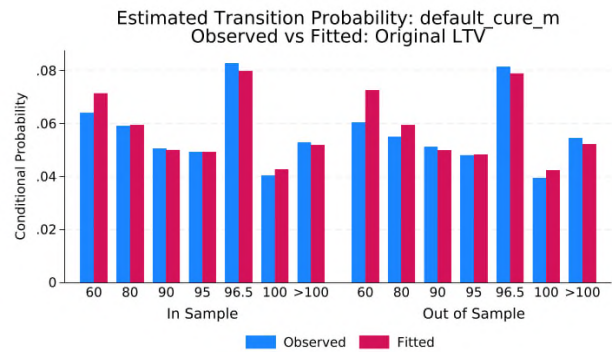
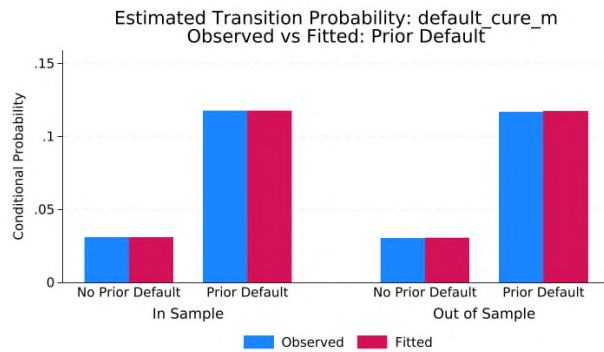
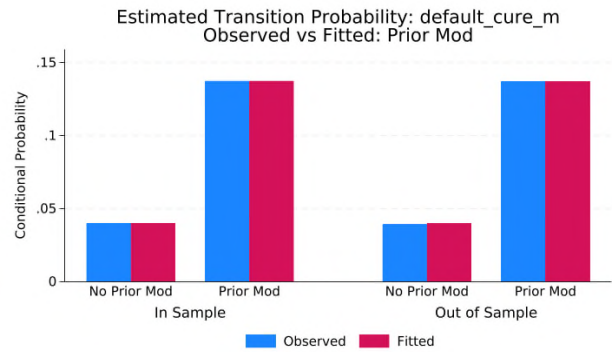
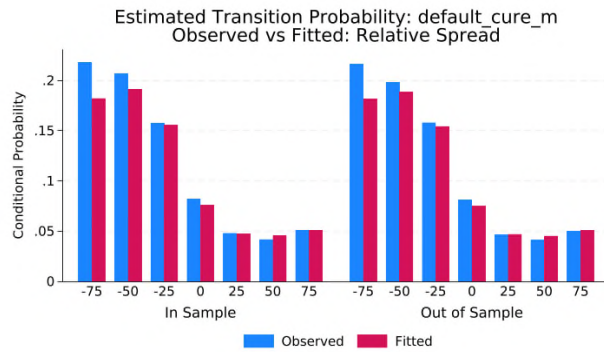


## Product 1 - default\_claim

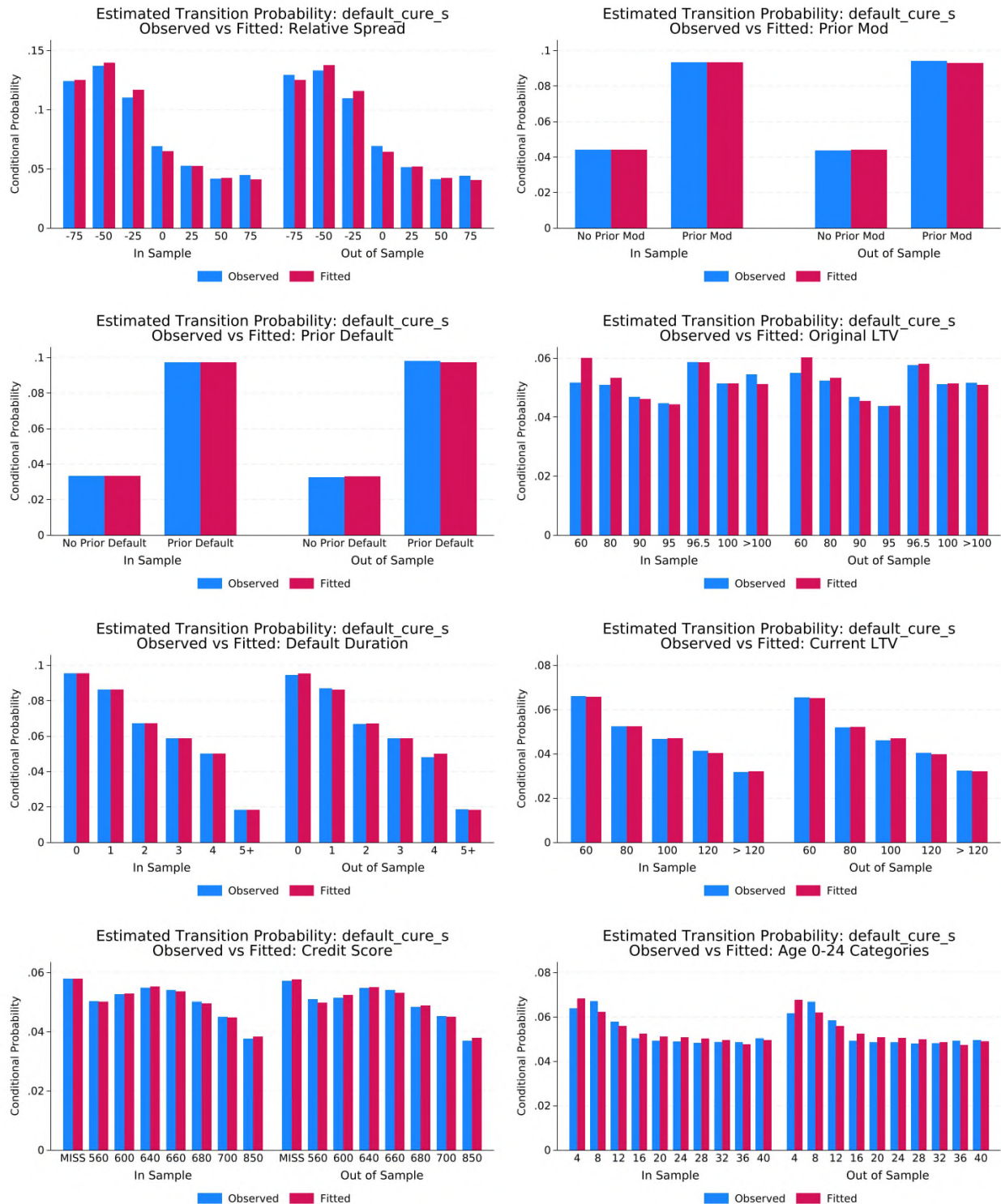




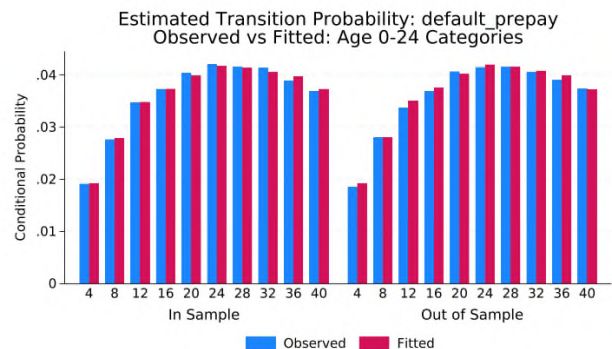
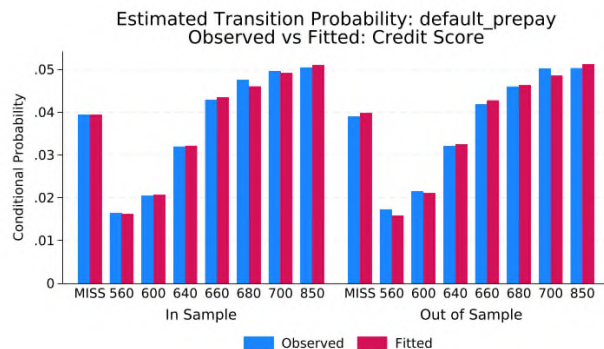
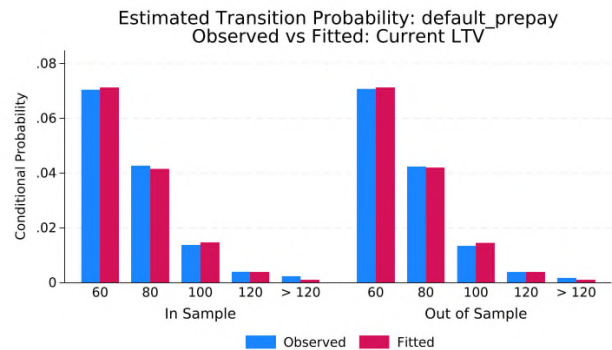
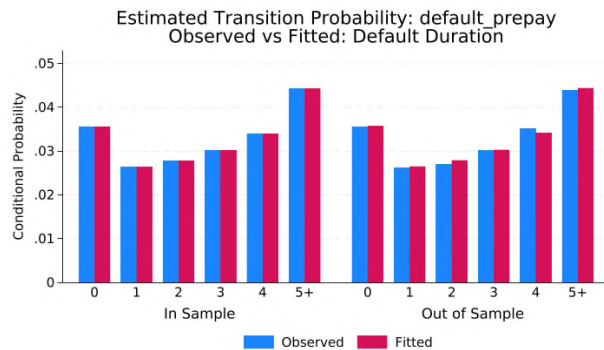
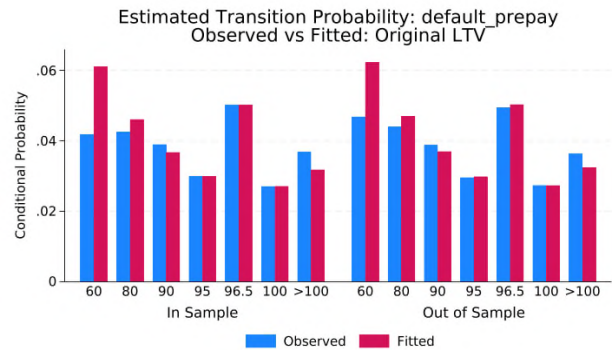
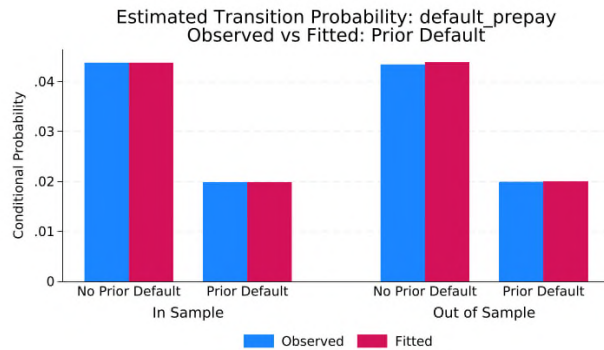
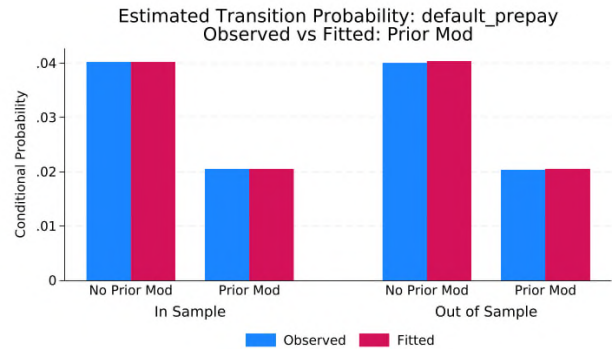
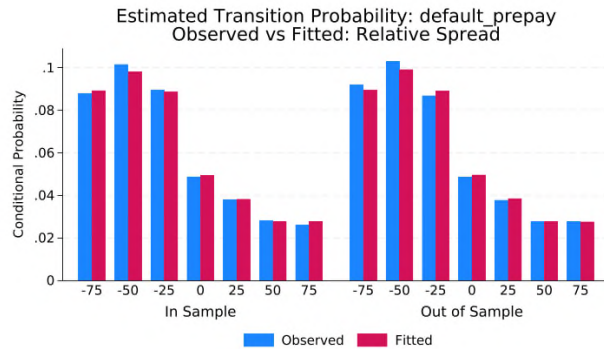
Product 1 - default\_cure\_m



## Product 1 - default\_cure\_s

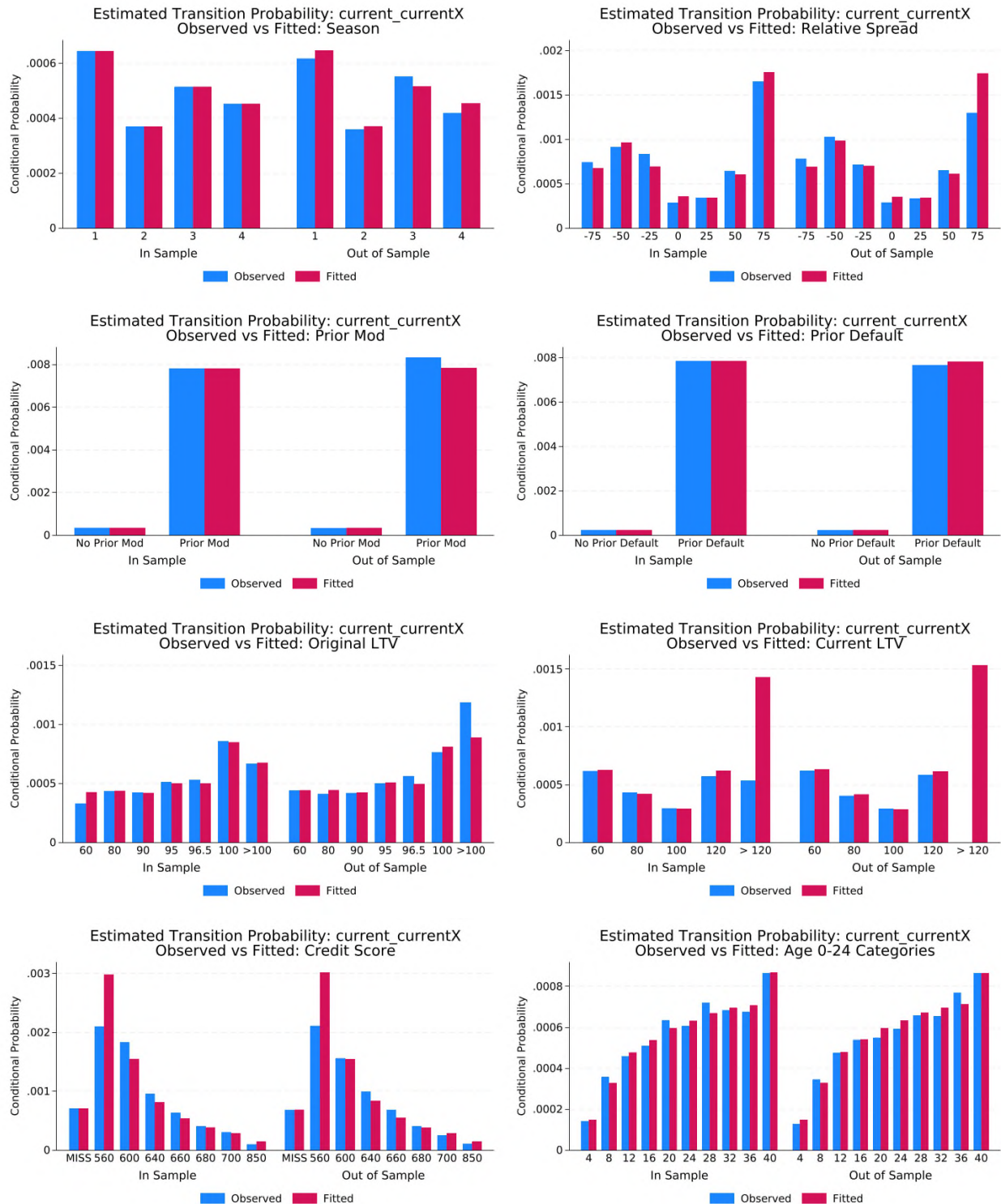


## Product 1 - default\_prepay



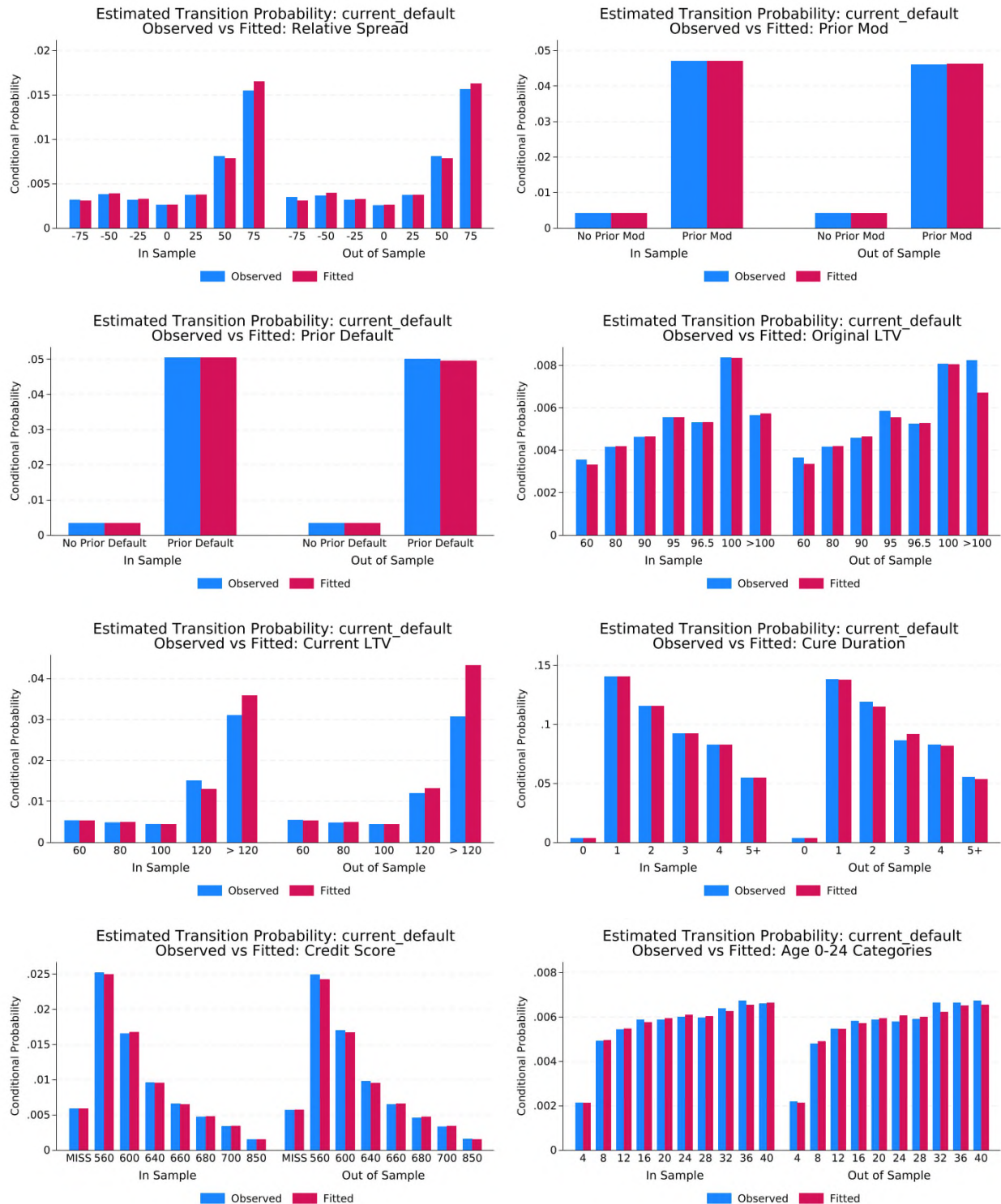


## Product 2 - current\_currentX

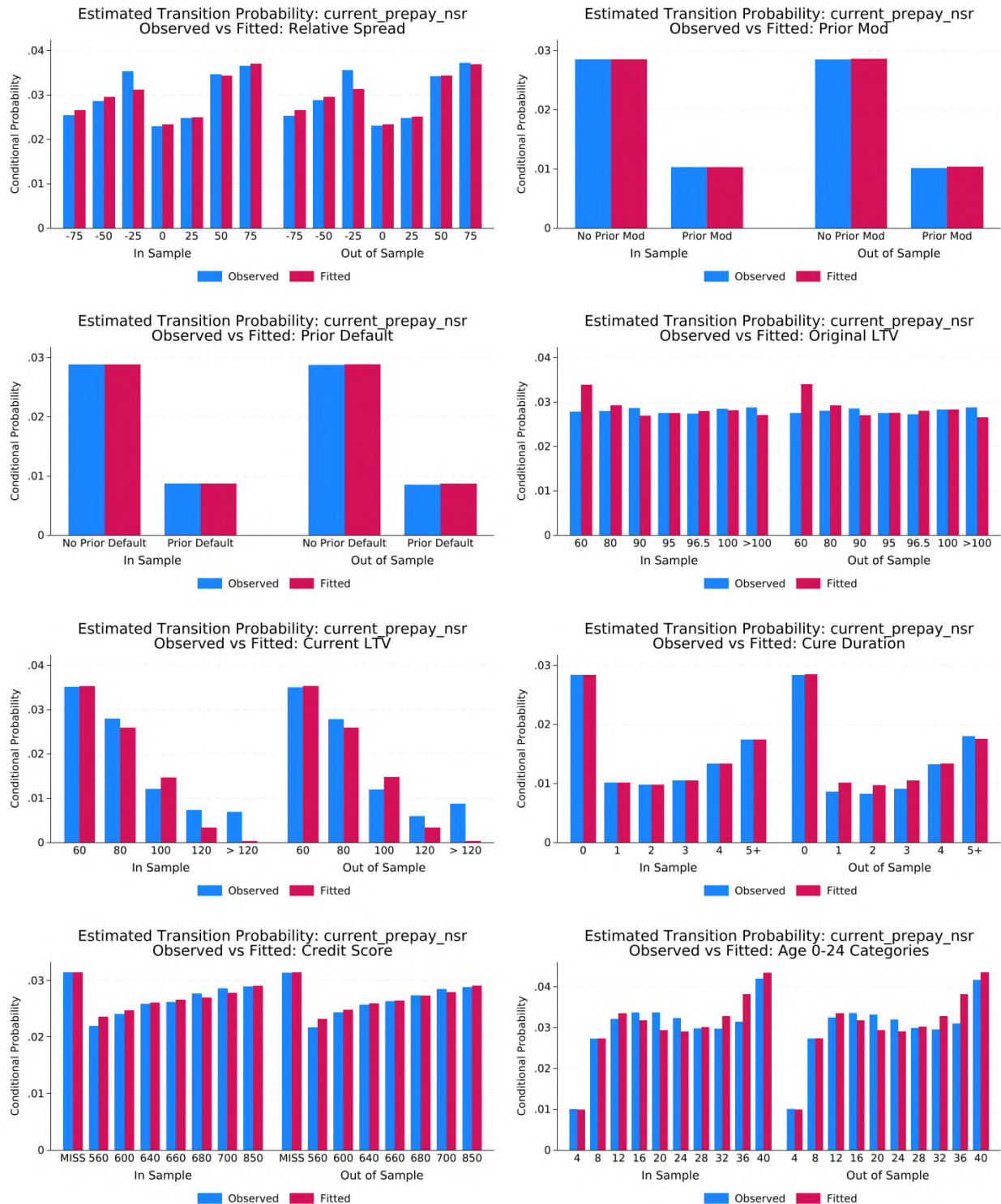




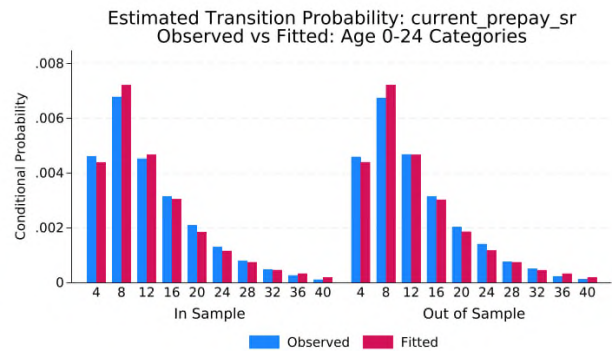
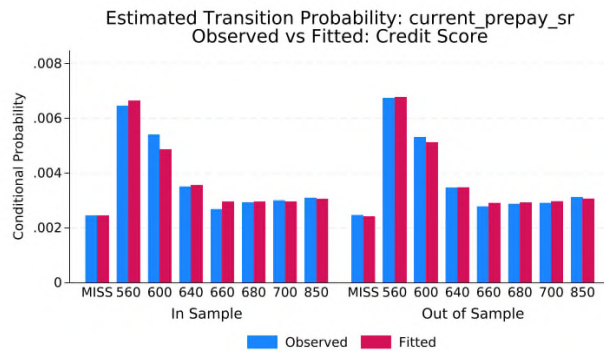
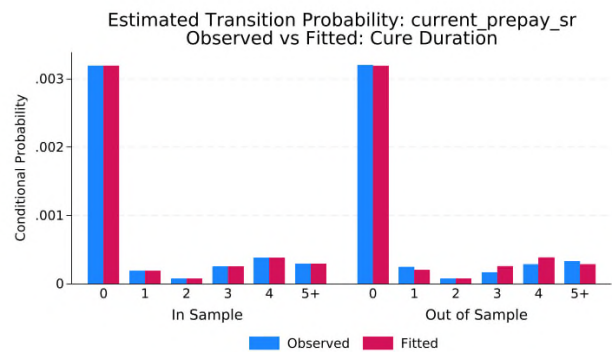
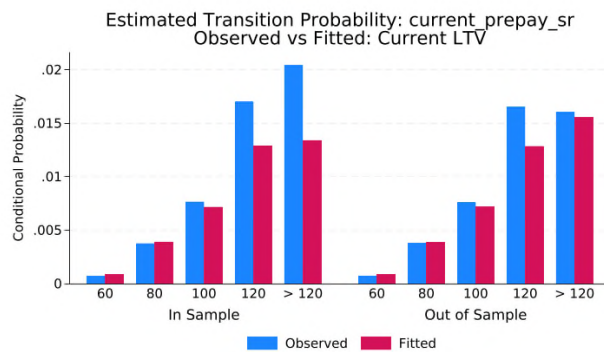
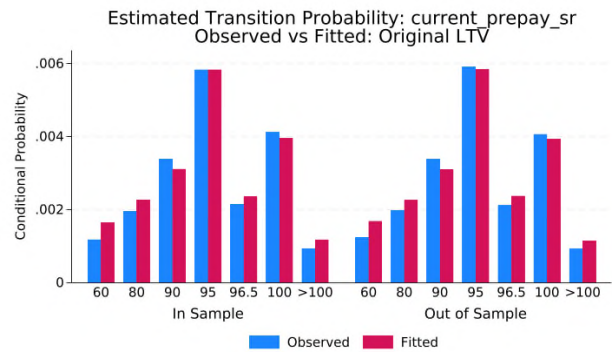
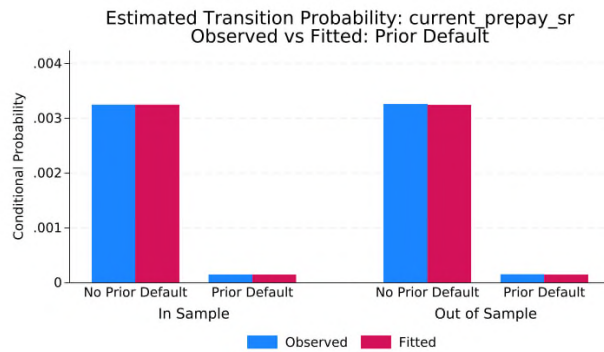
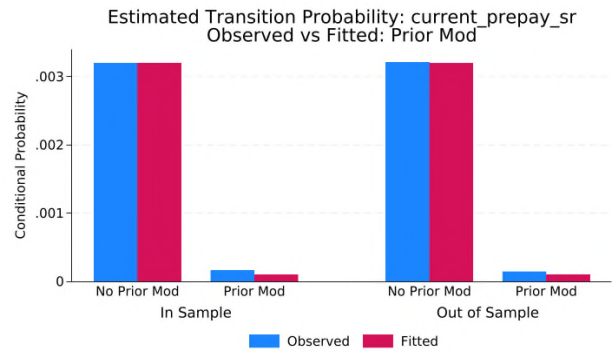
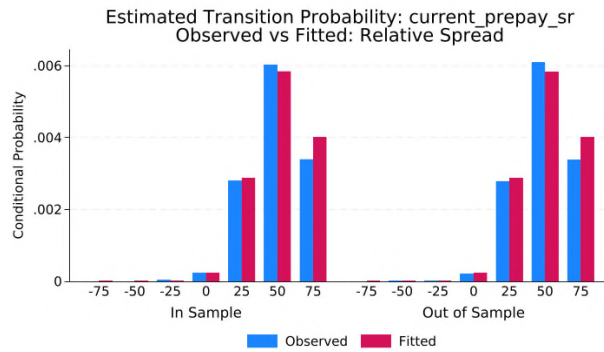
## Product 2 - current\_default



## Product 2 - current\_prepay\_nsr

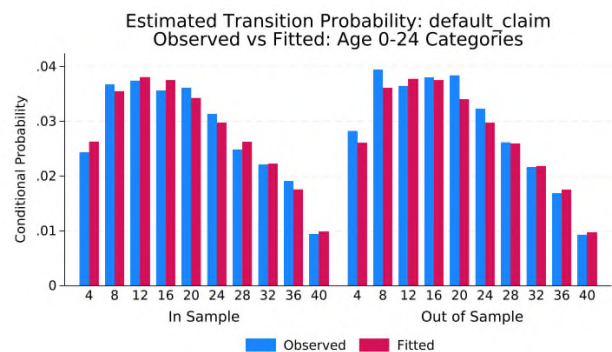
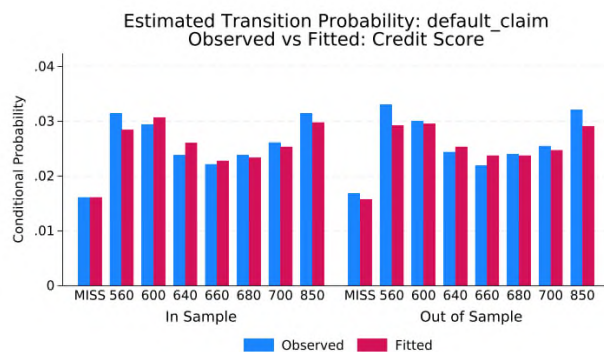
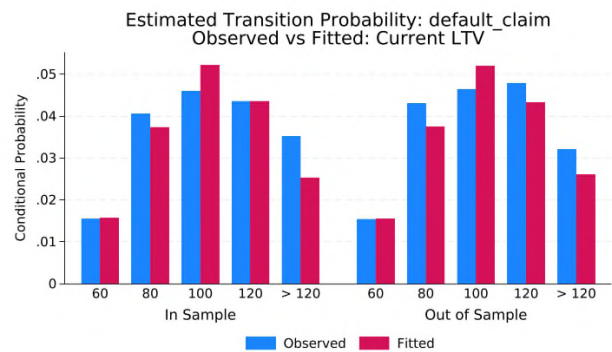
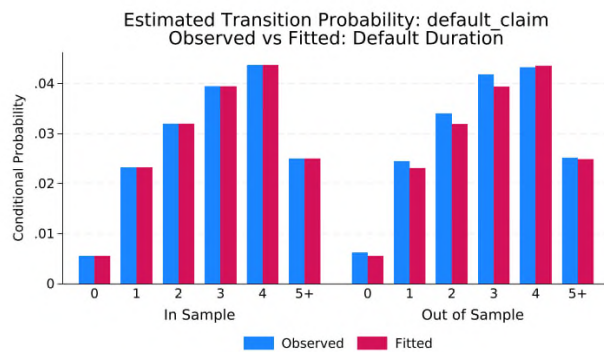
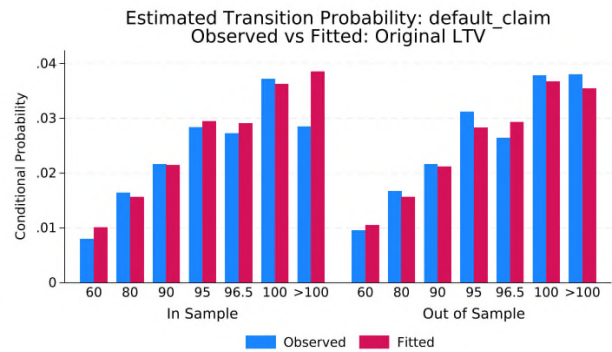
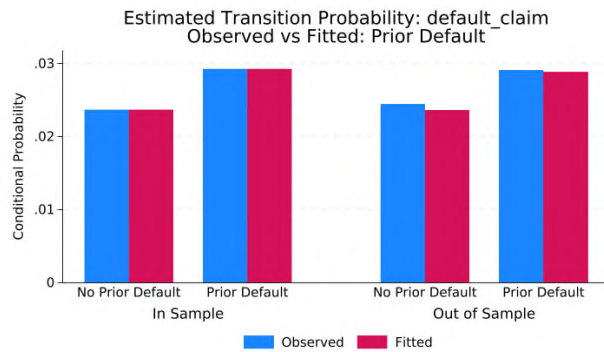
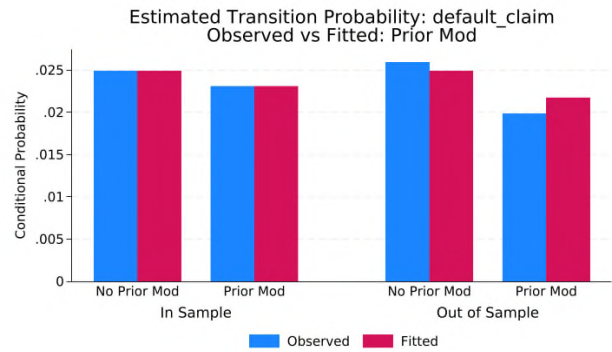
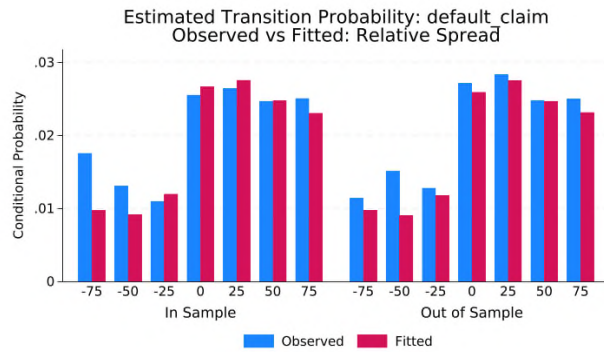


## Product 2 - current\_prepay\_sr

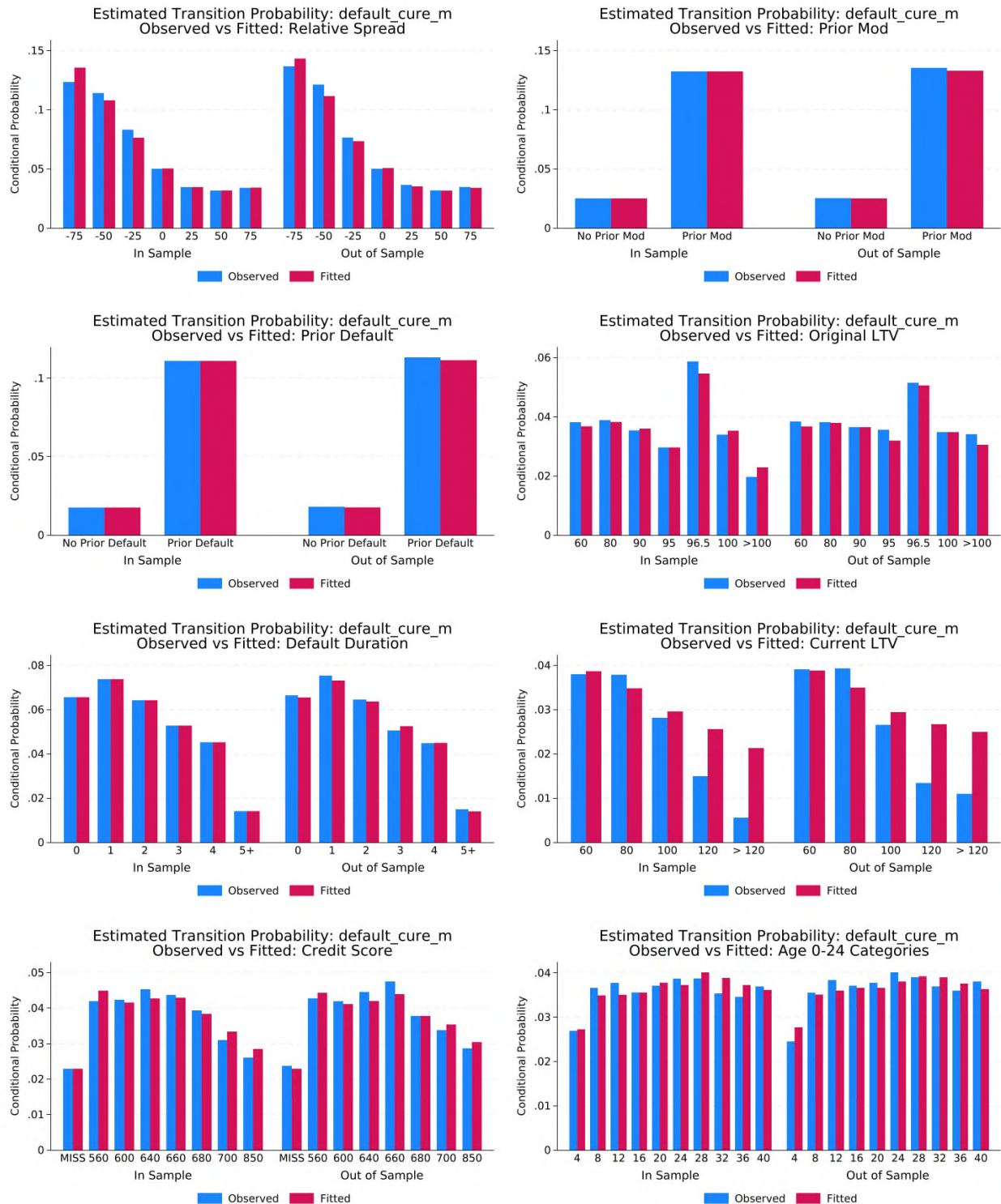




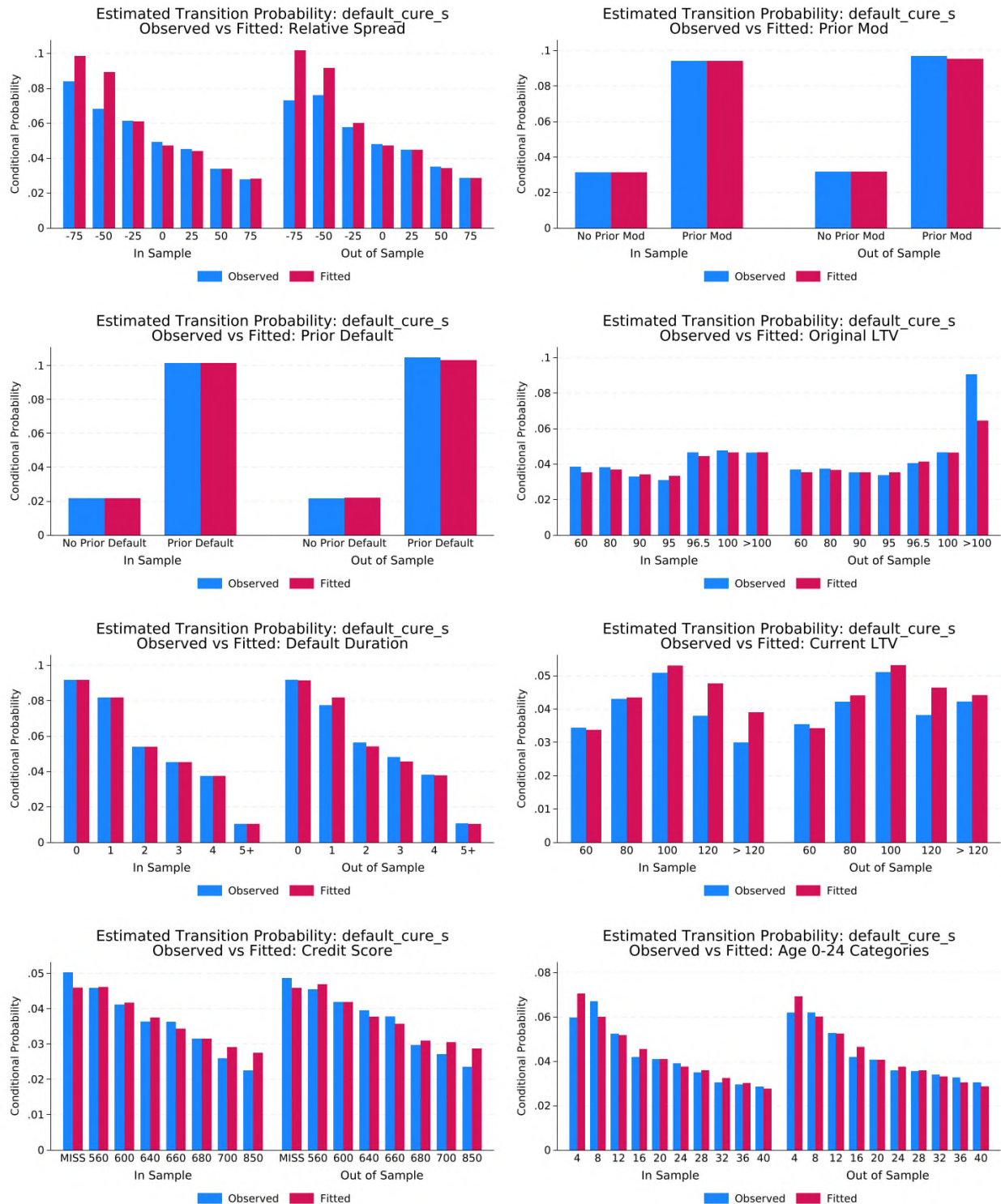
## Product 2 - default\_claim



## Product 2 - default\_cure\_m

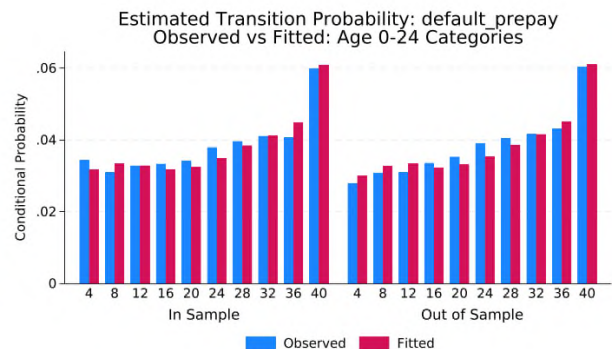
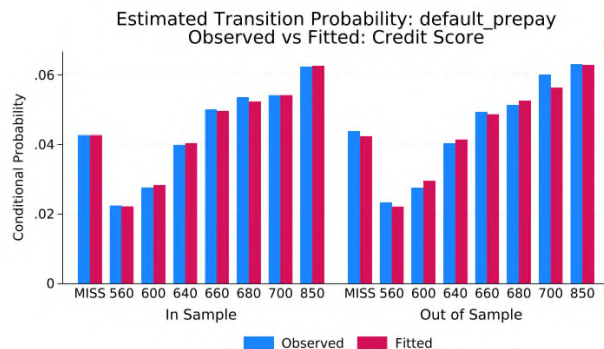
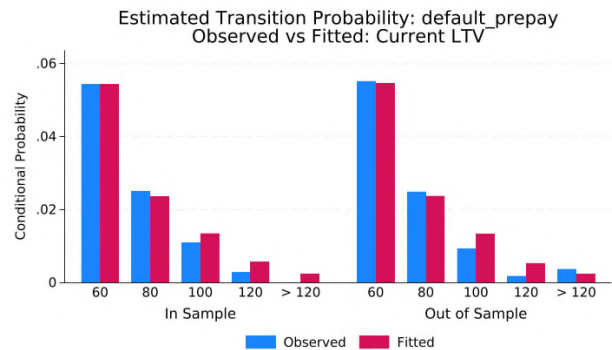
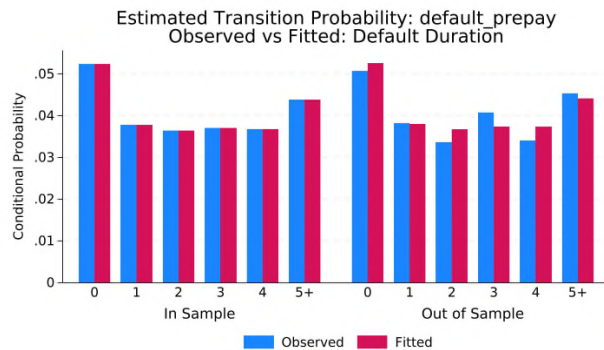
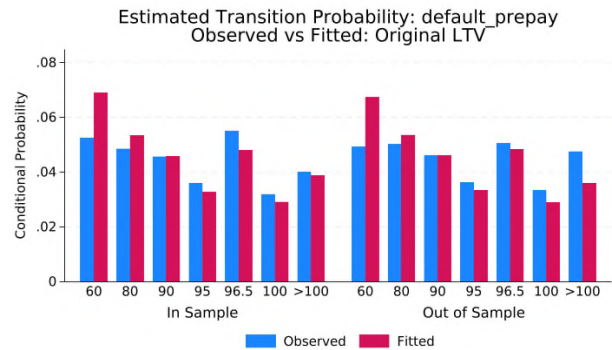
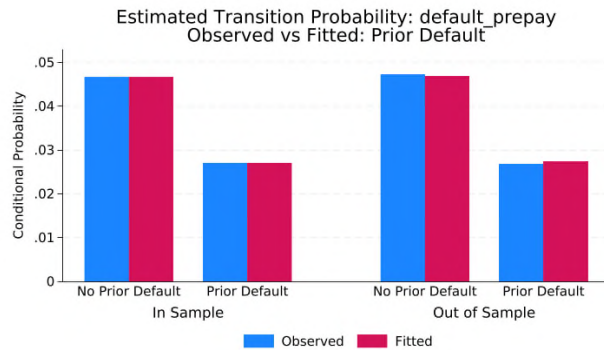
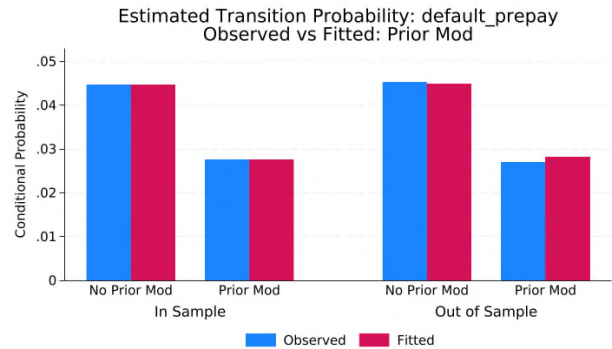
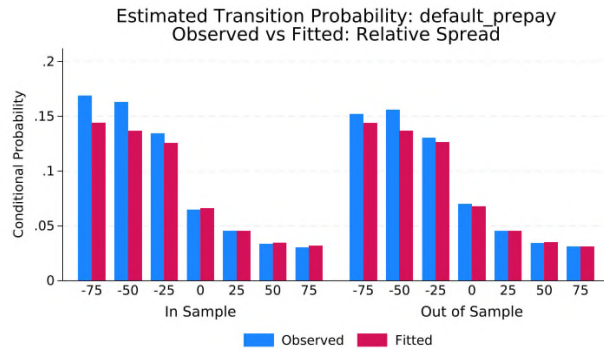


## Product 2 - default\_cure\_s

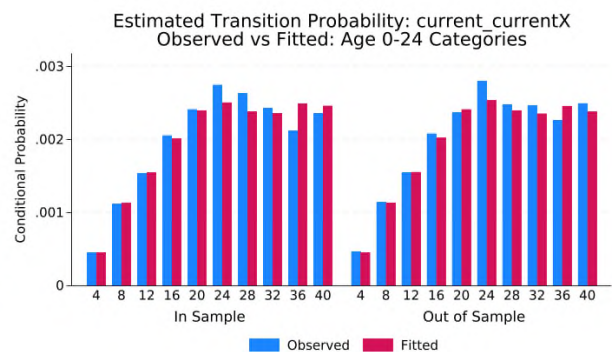
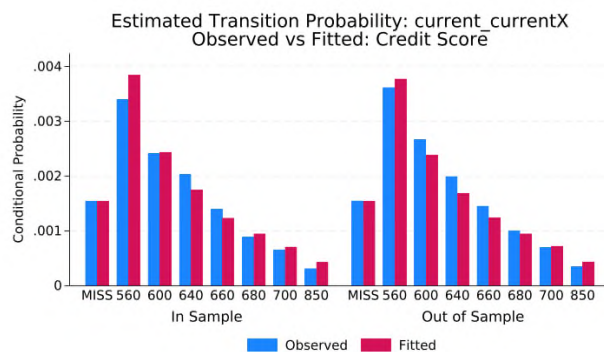
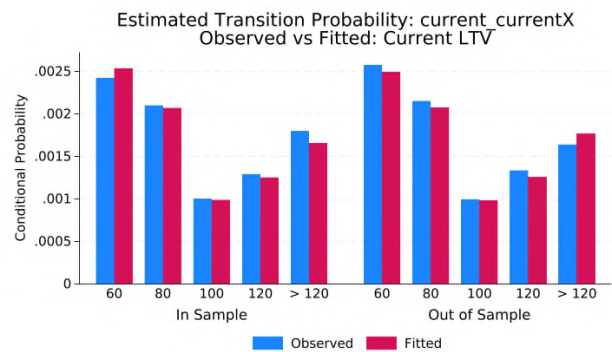
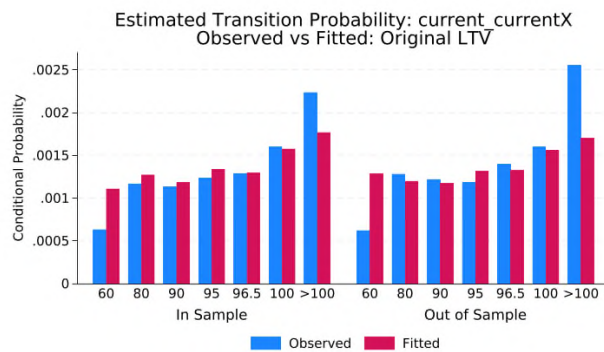
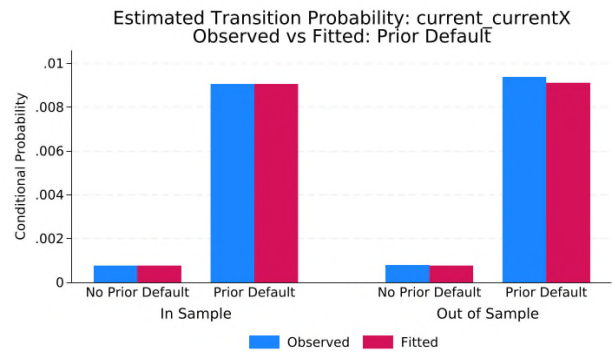
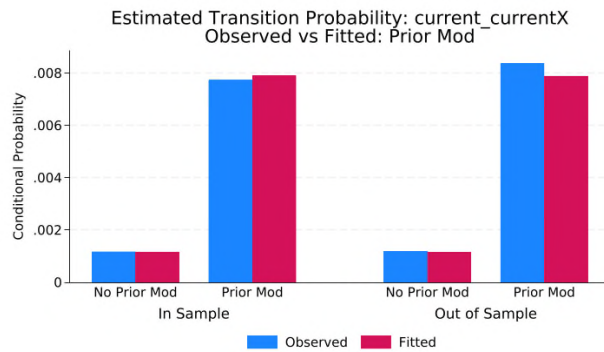
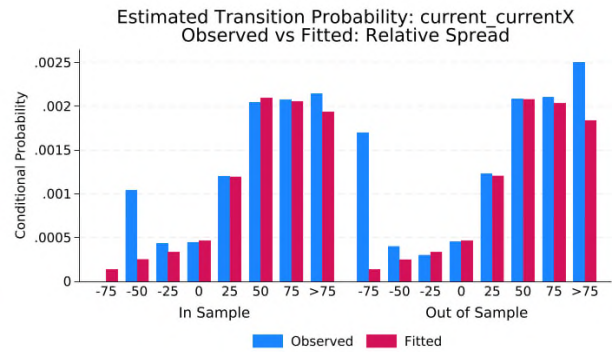
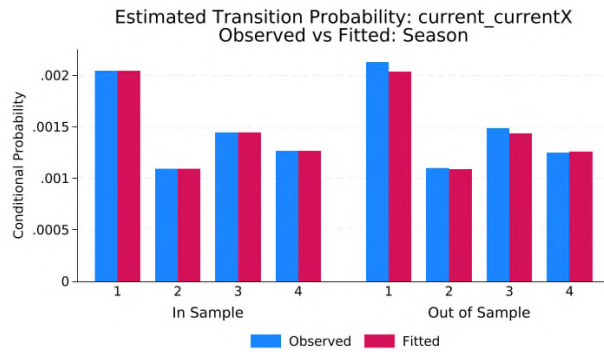




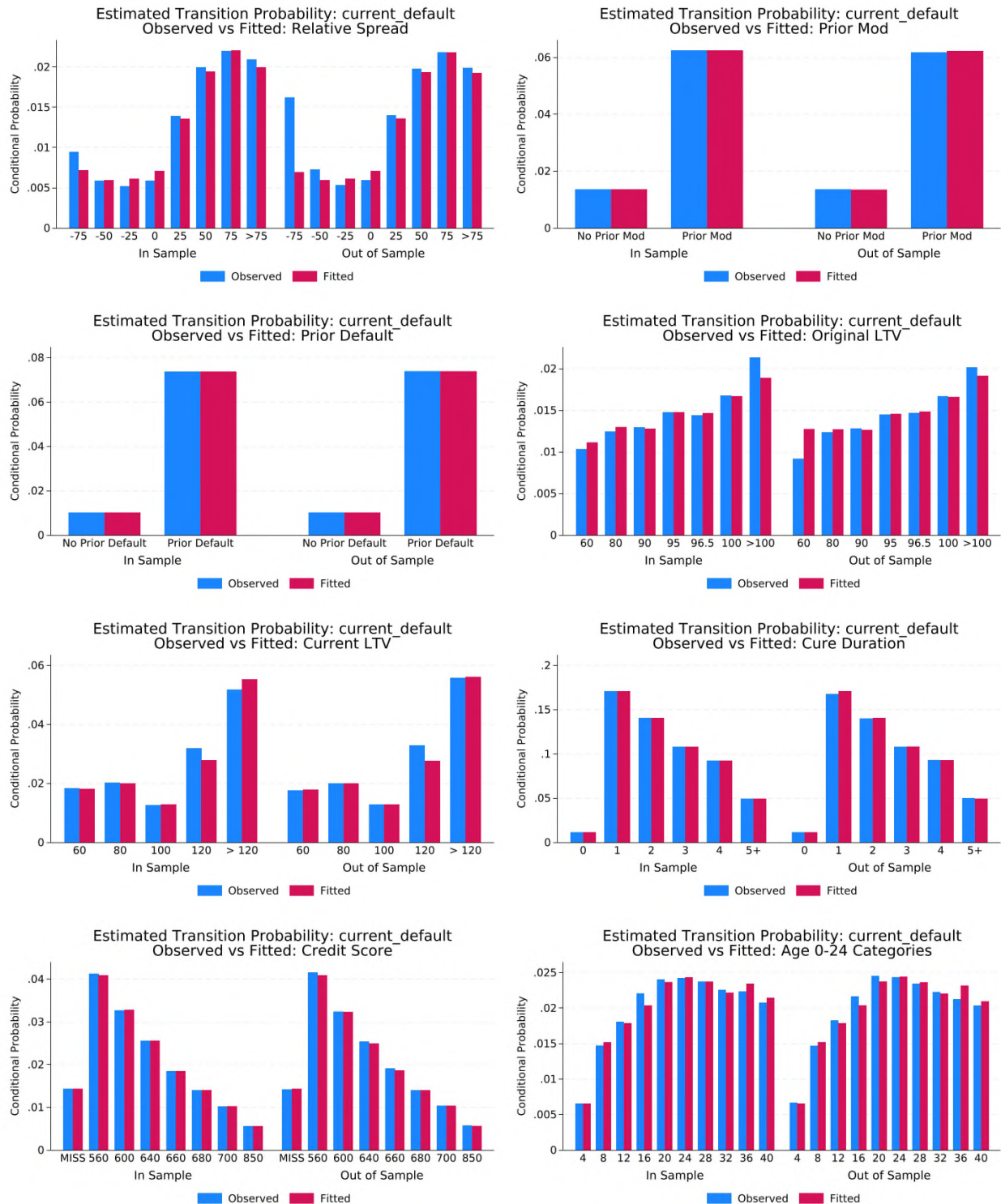
## Product 2 - default\_prepay



### Product 3 - current\_currentX

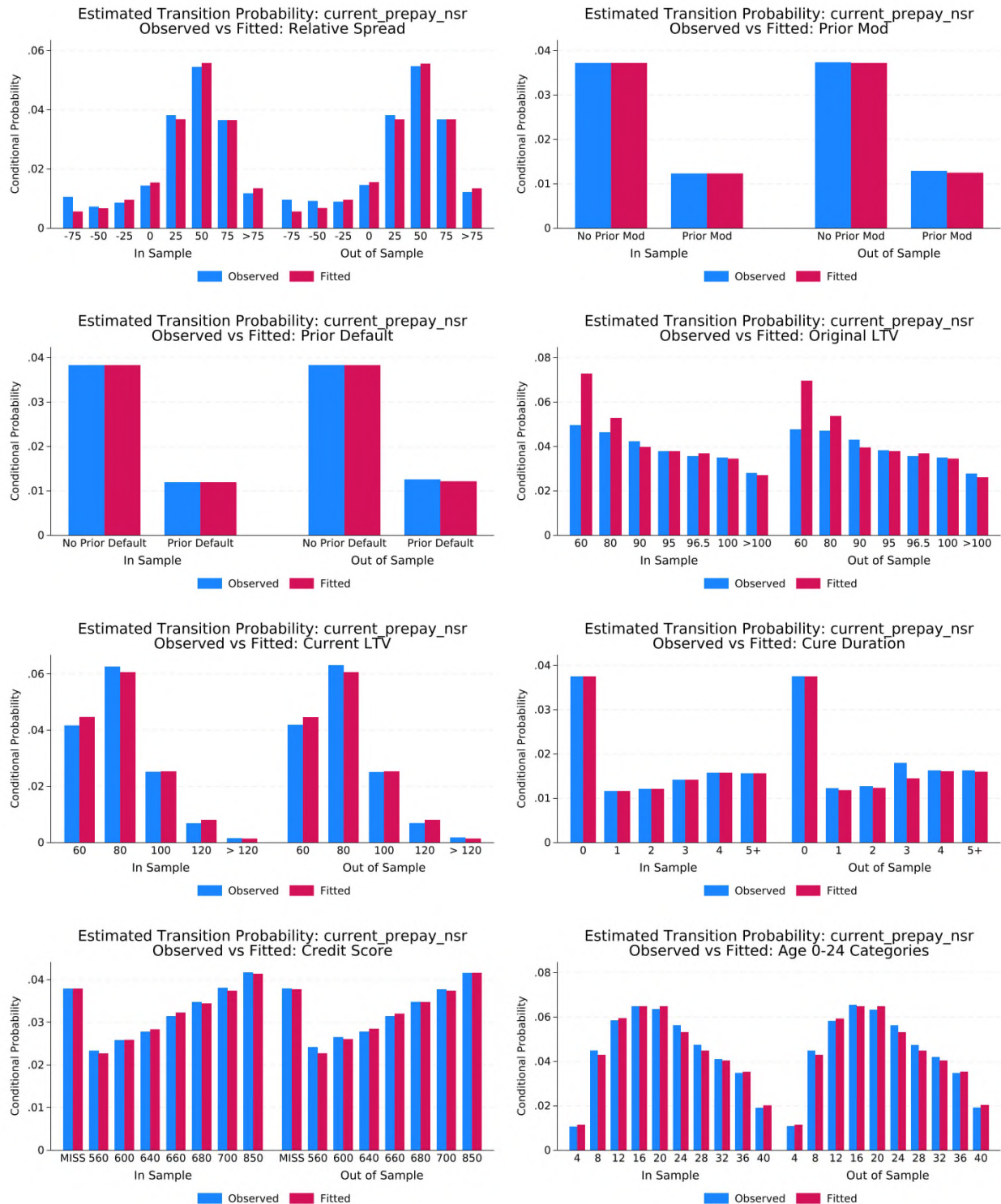


### Product 3 - current\_default

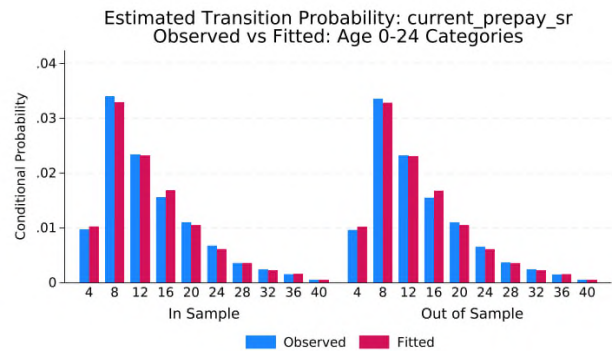
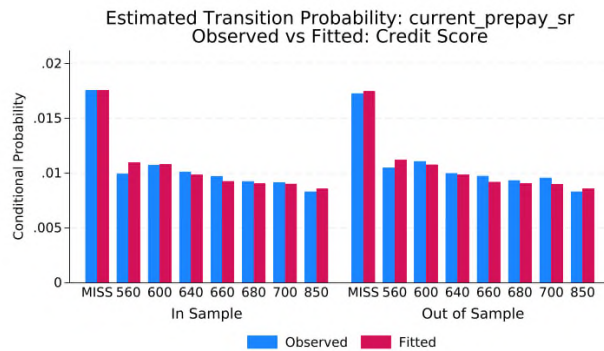
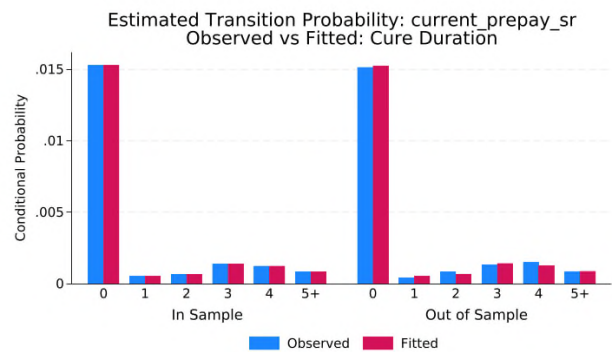
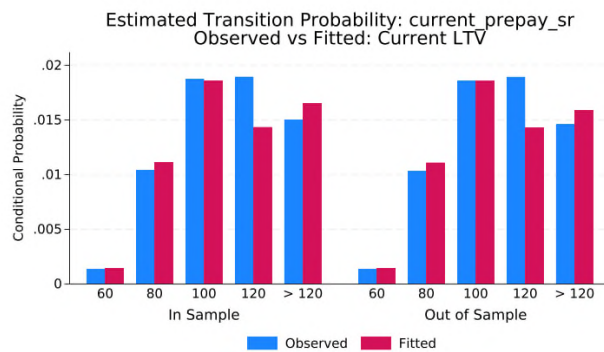
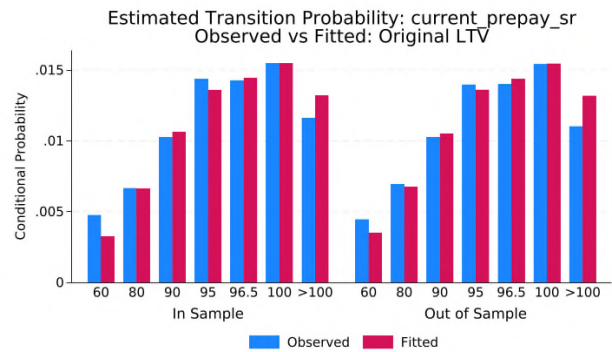
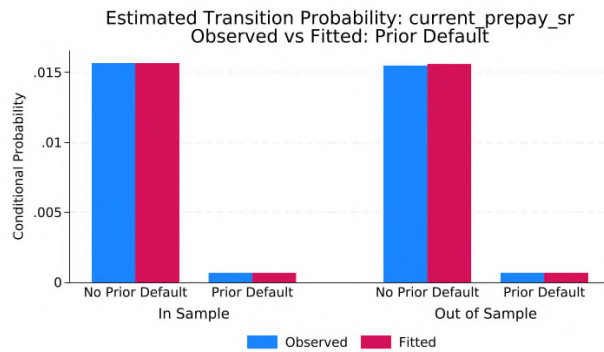
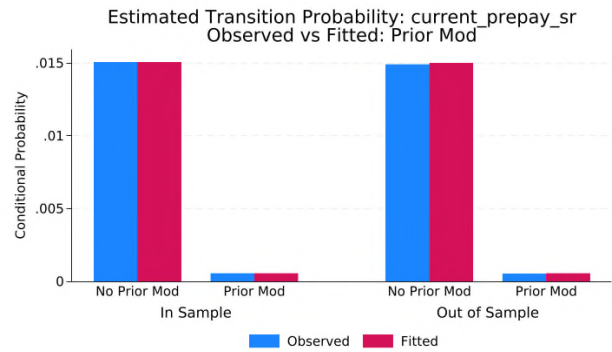
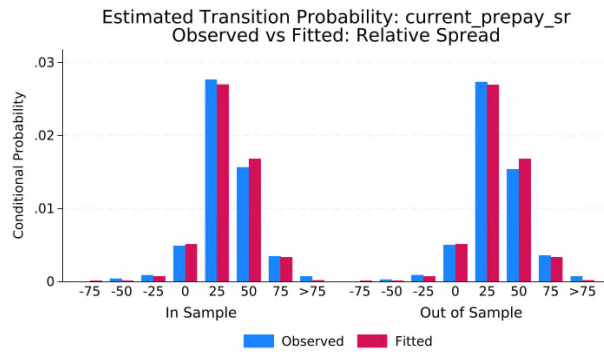




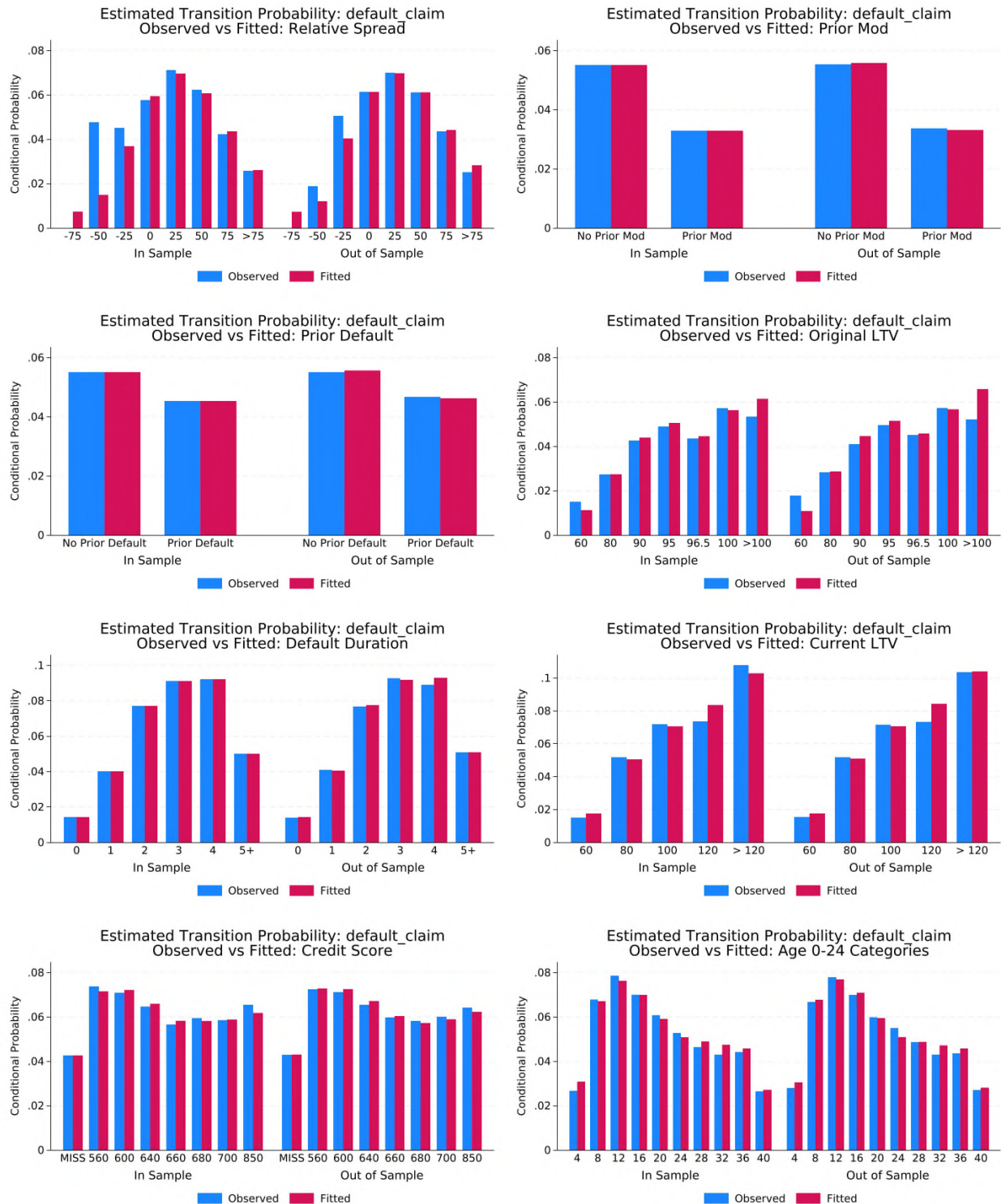
### Product 3 - current\_prepay\_nsr



### Product 3 - current\_prepay\_sr

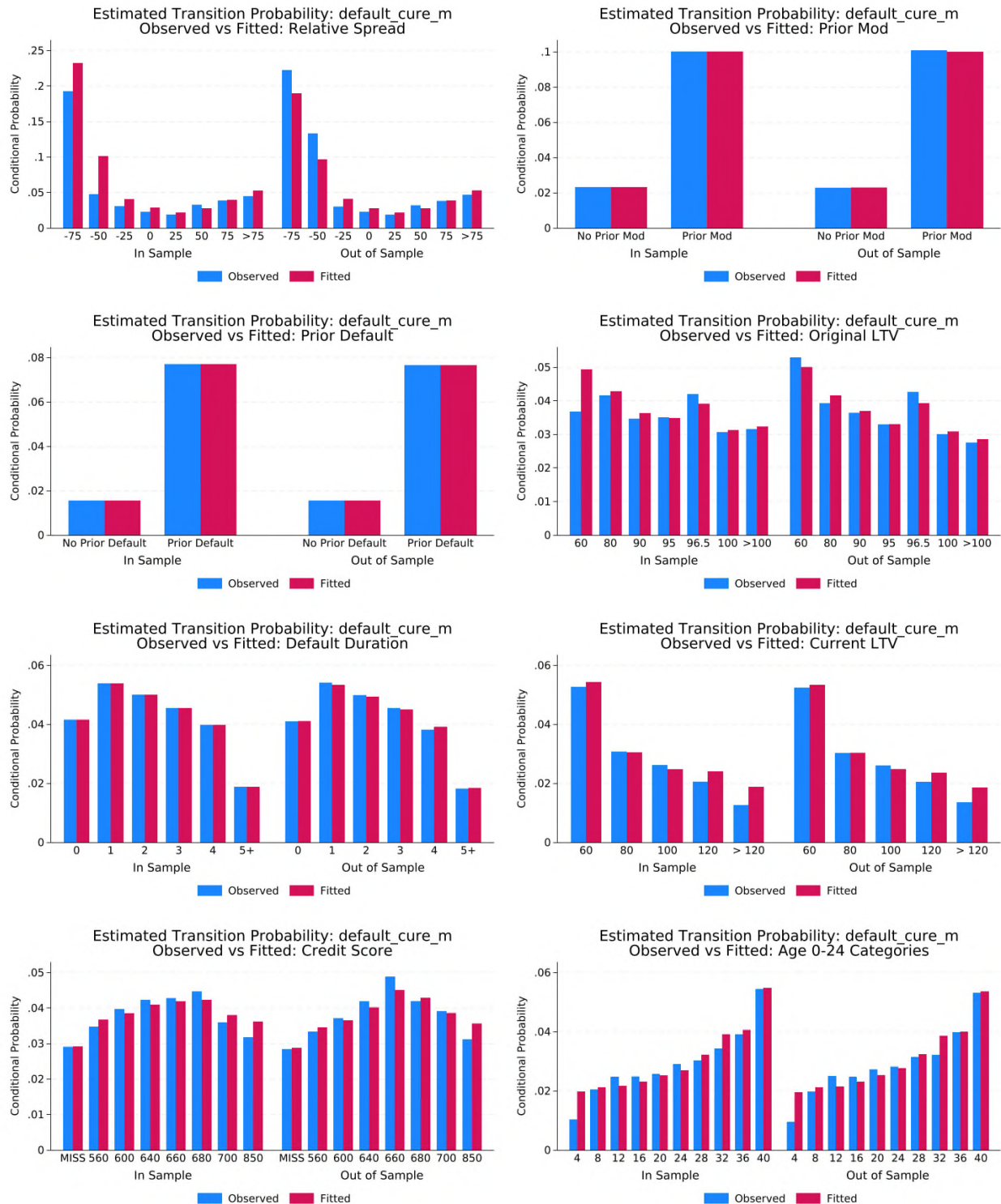


### Product 3 - default\_claim

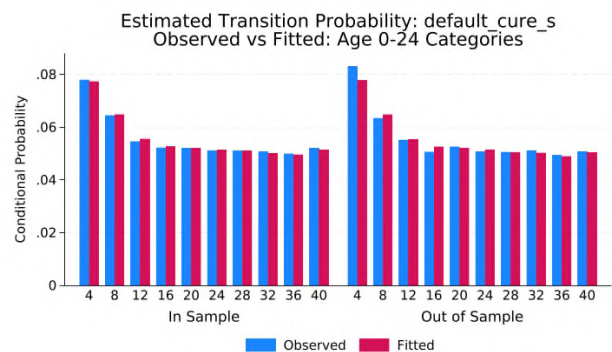
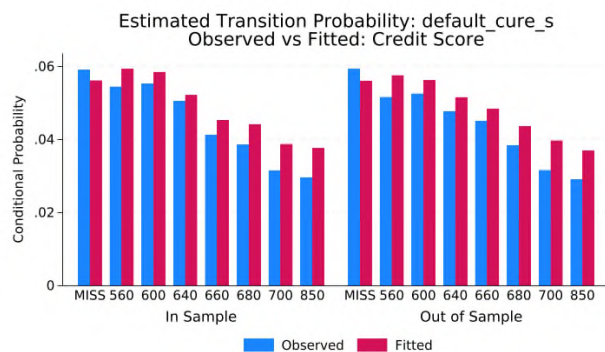
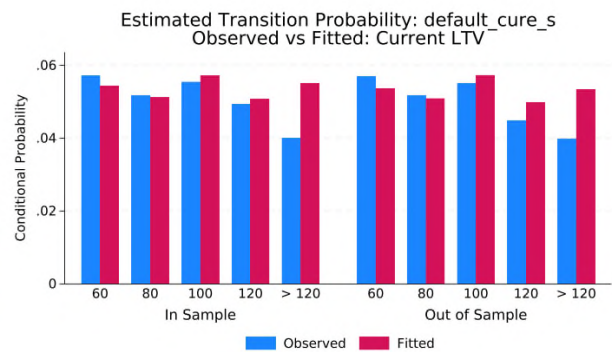
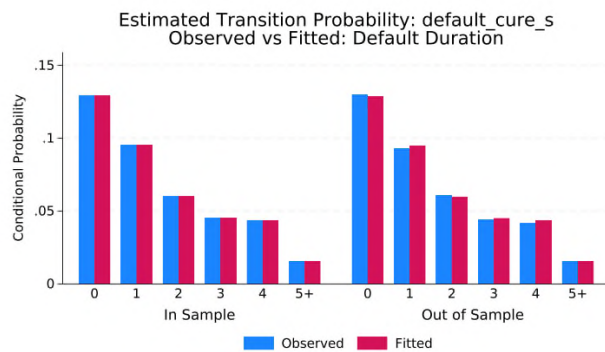
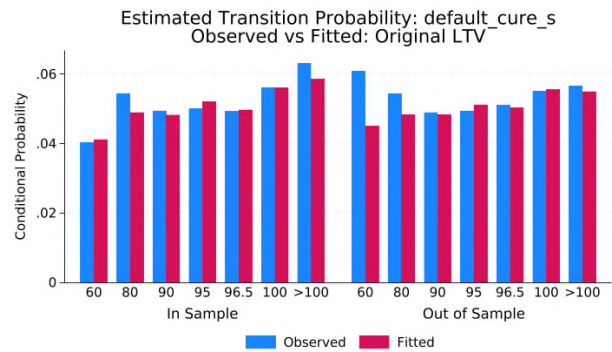
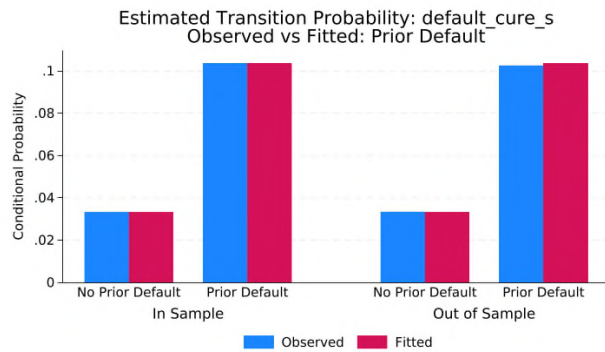
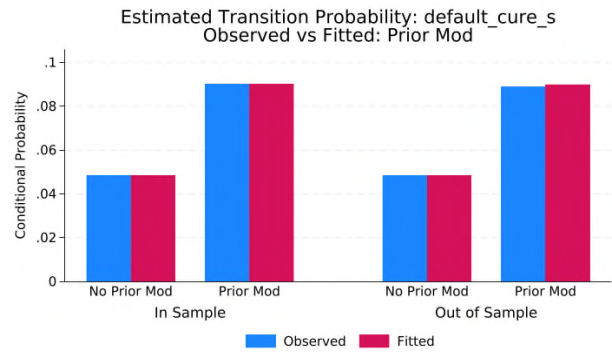
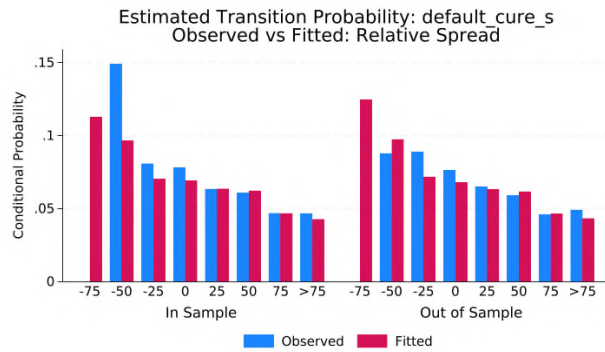




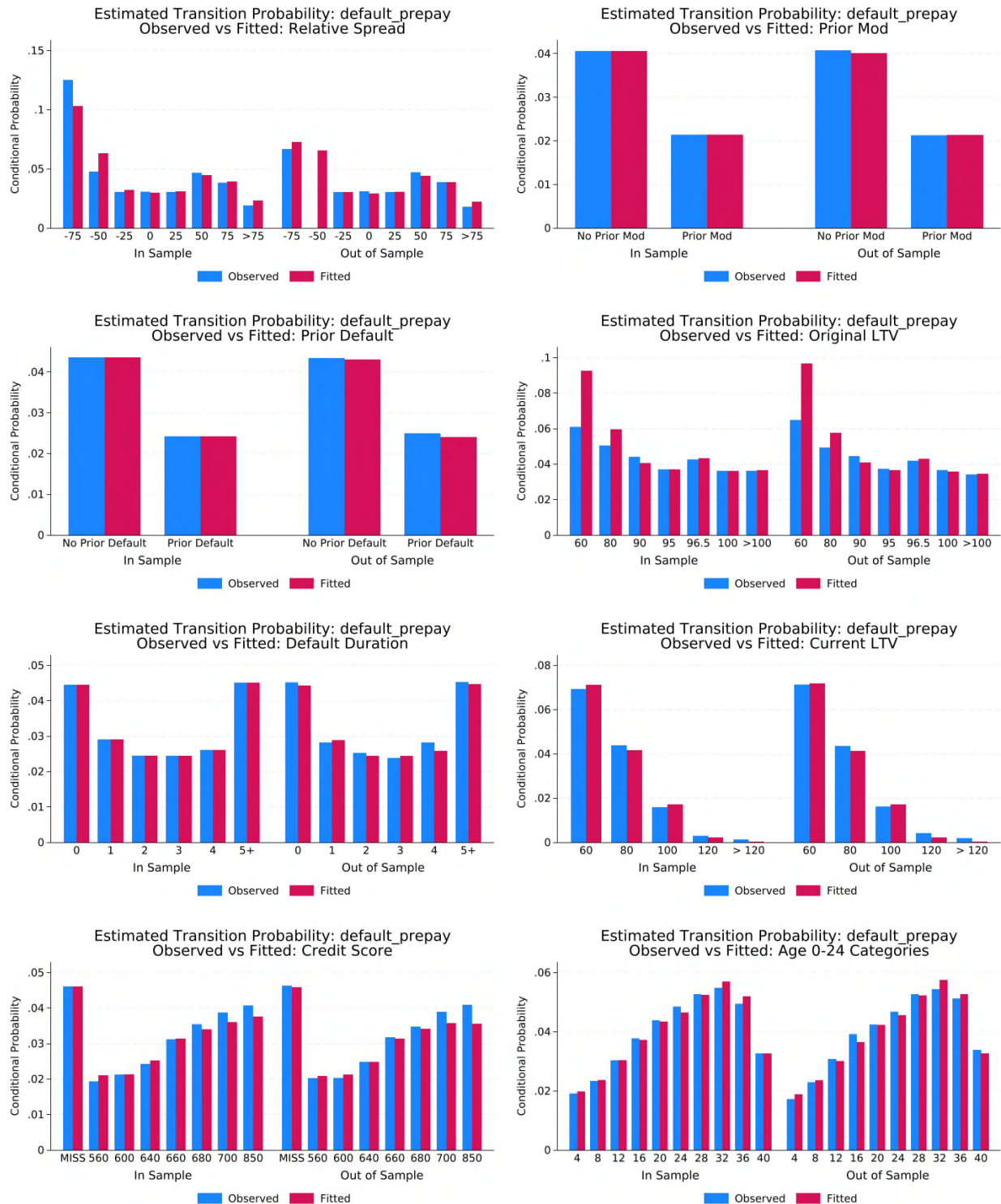
### Product 3 - default\_cure\_m



### Product 3 - default\_cure\_s

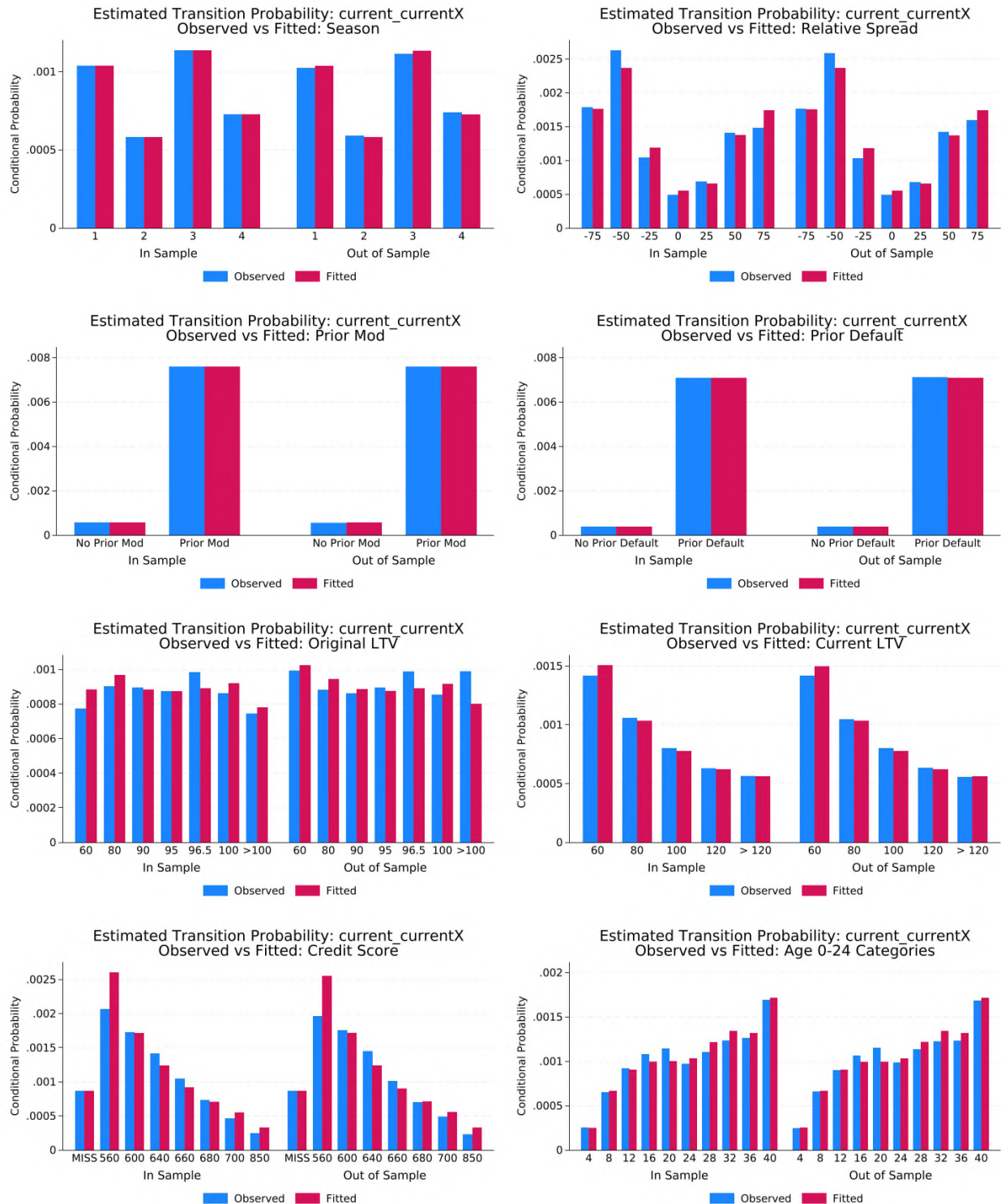


### Product 3 - default\_prepay

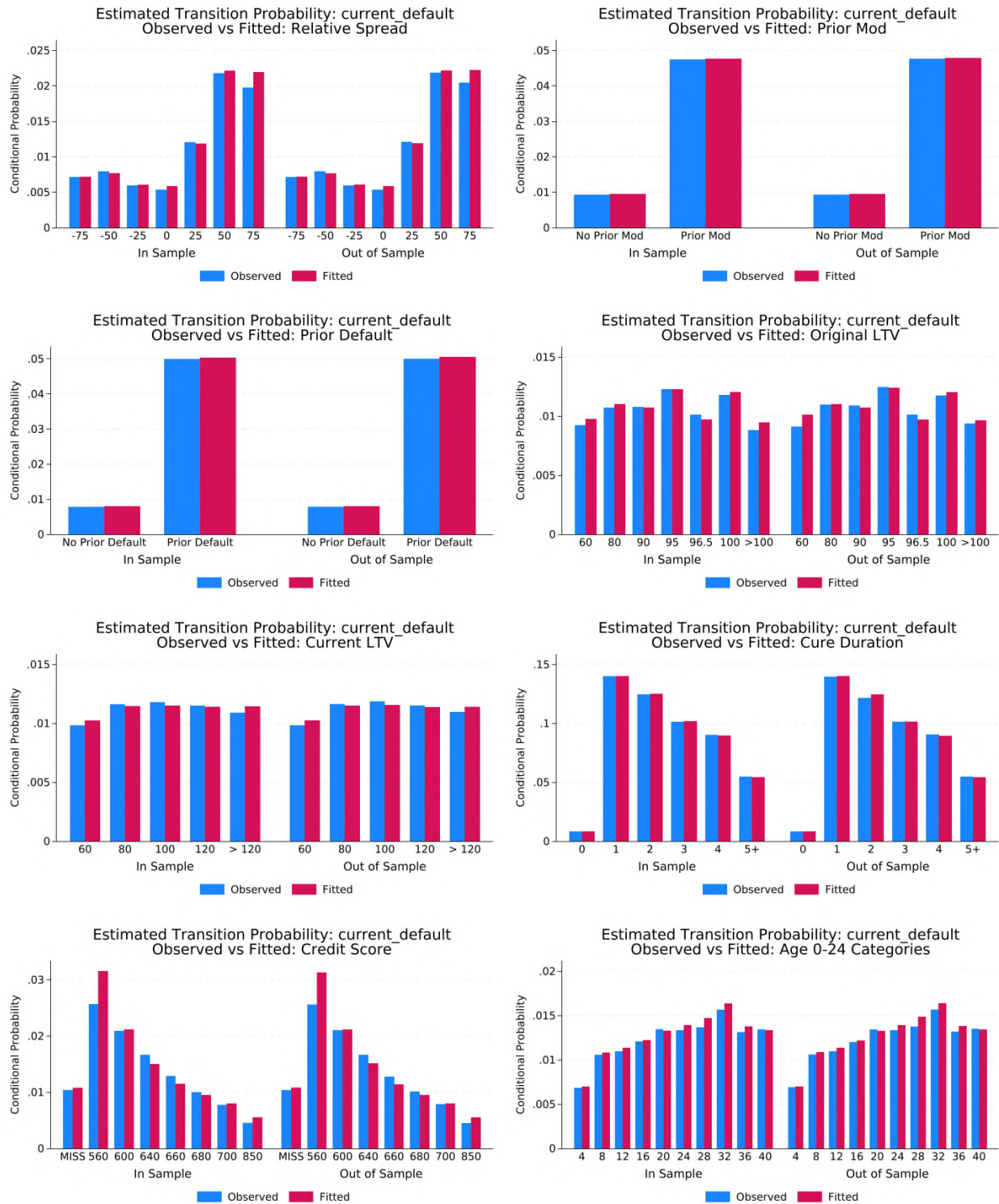




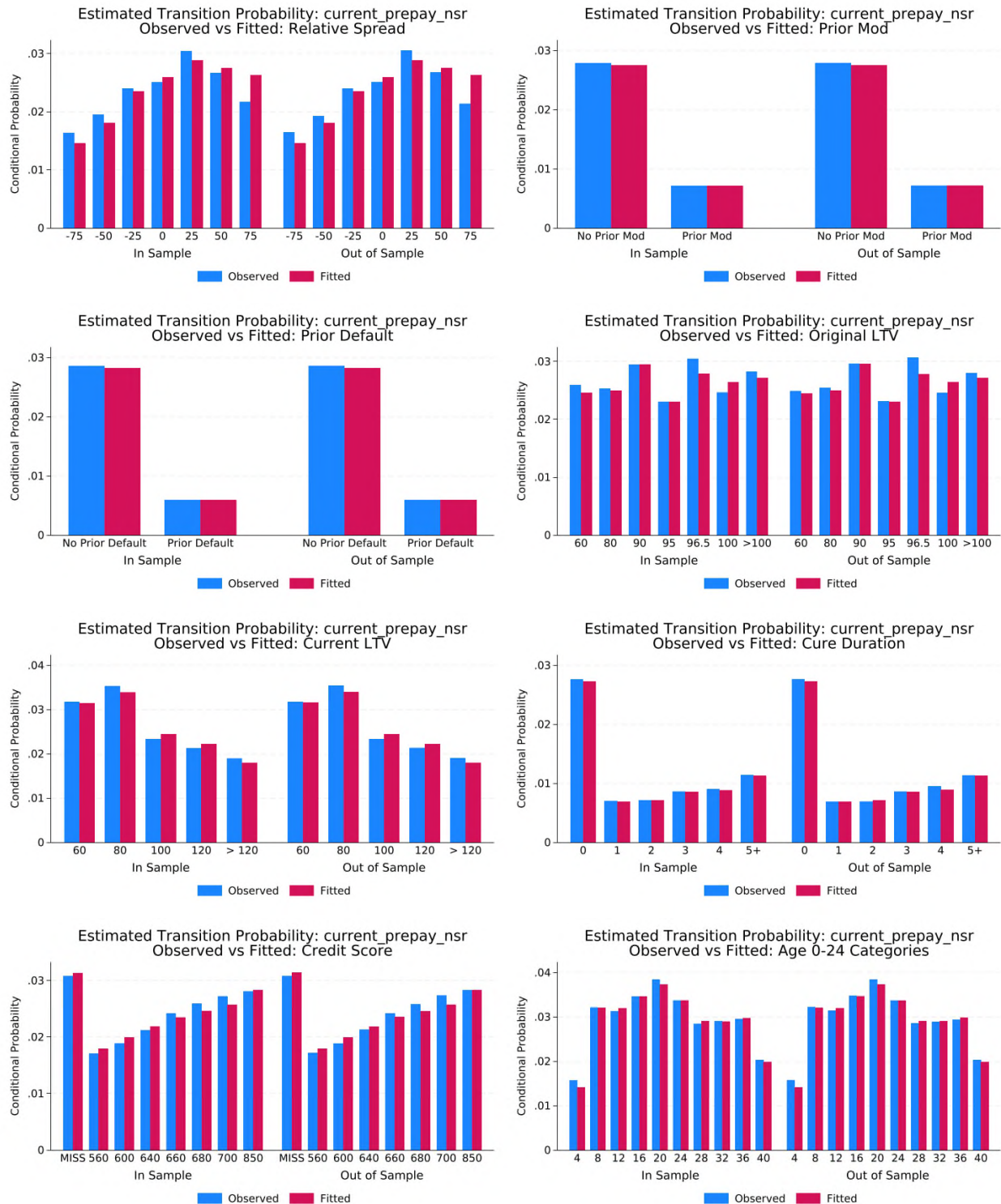
## Product 4 - current\_currentX



## Product 4 - current\_default

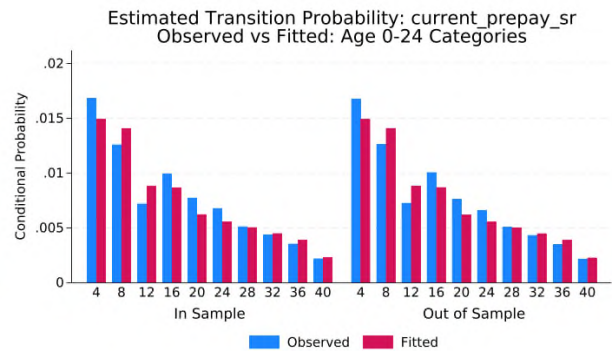
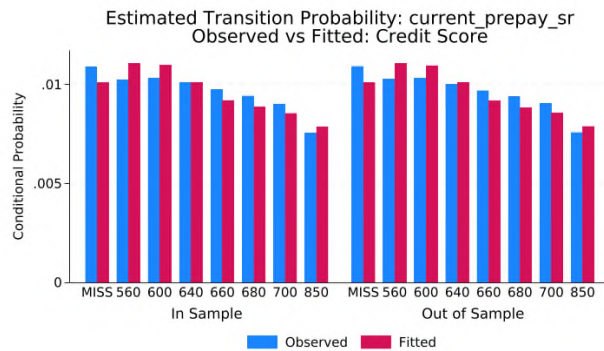
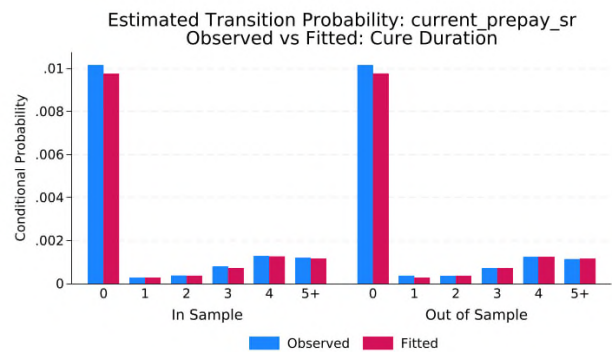
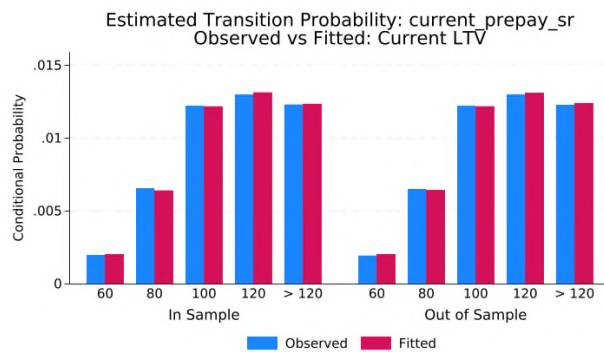
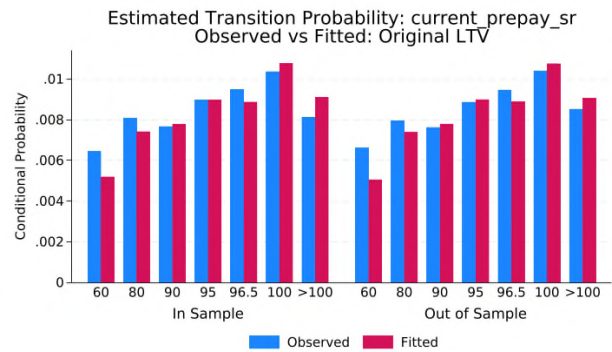
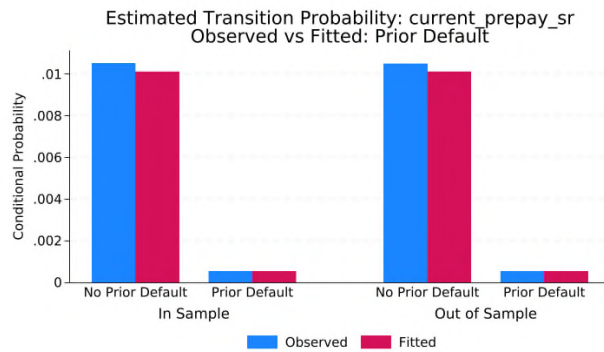
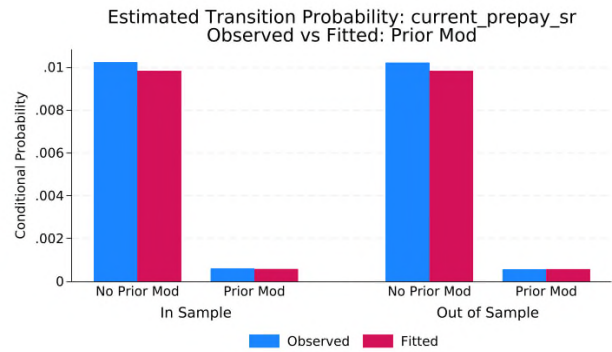
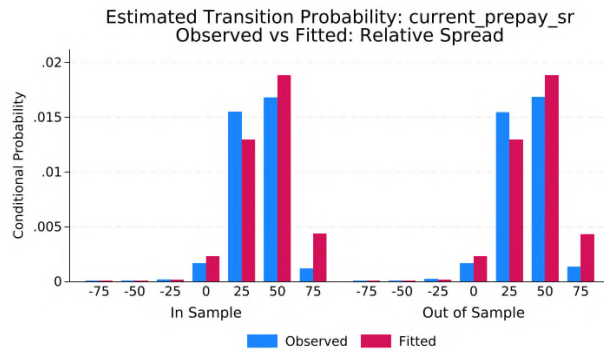


### Product 4 - current\_prepay\_nsr

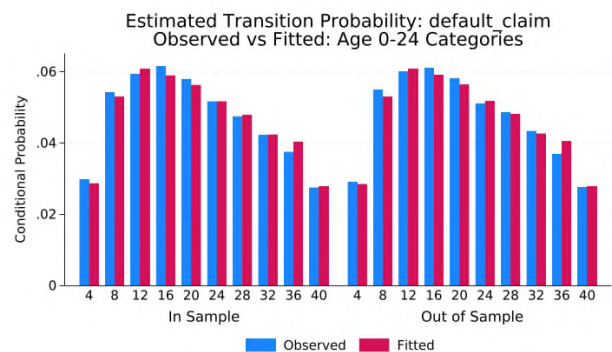
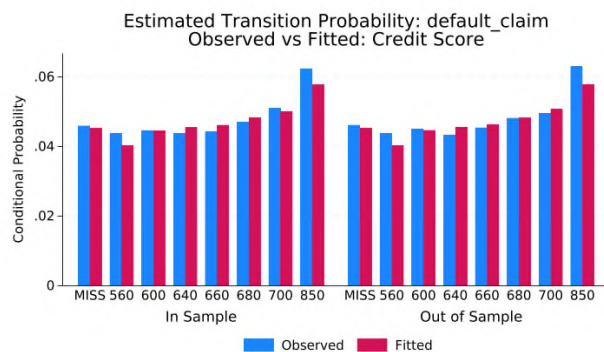
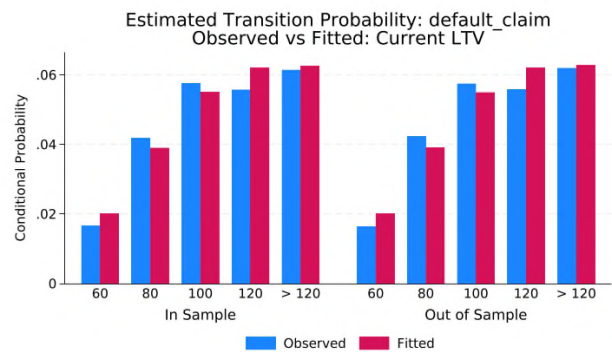
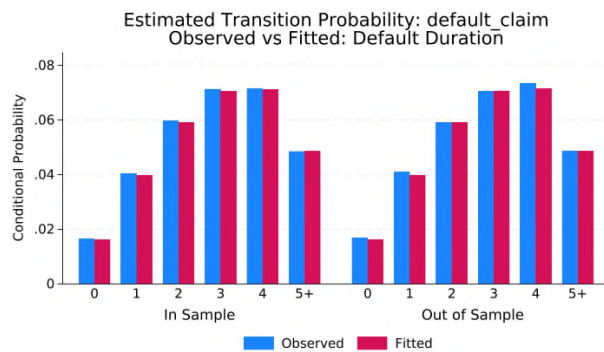
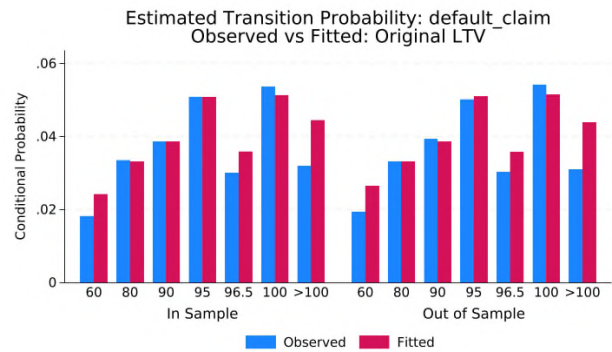
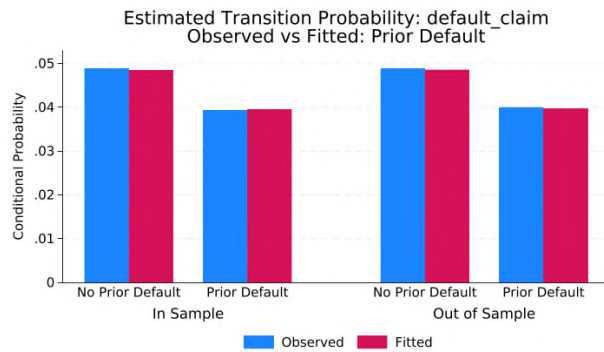
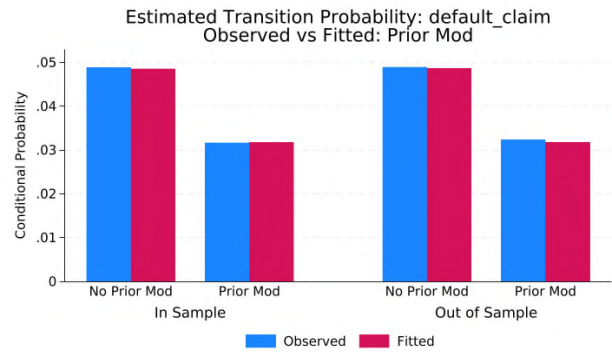
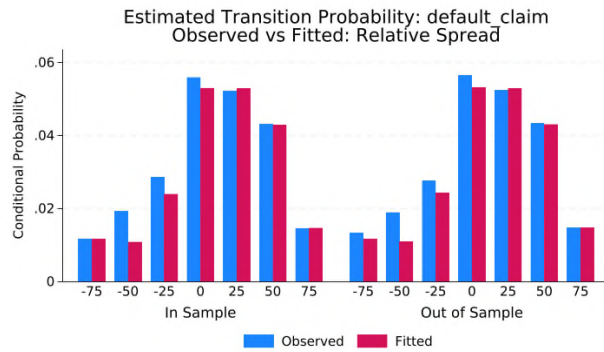




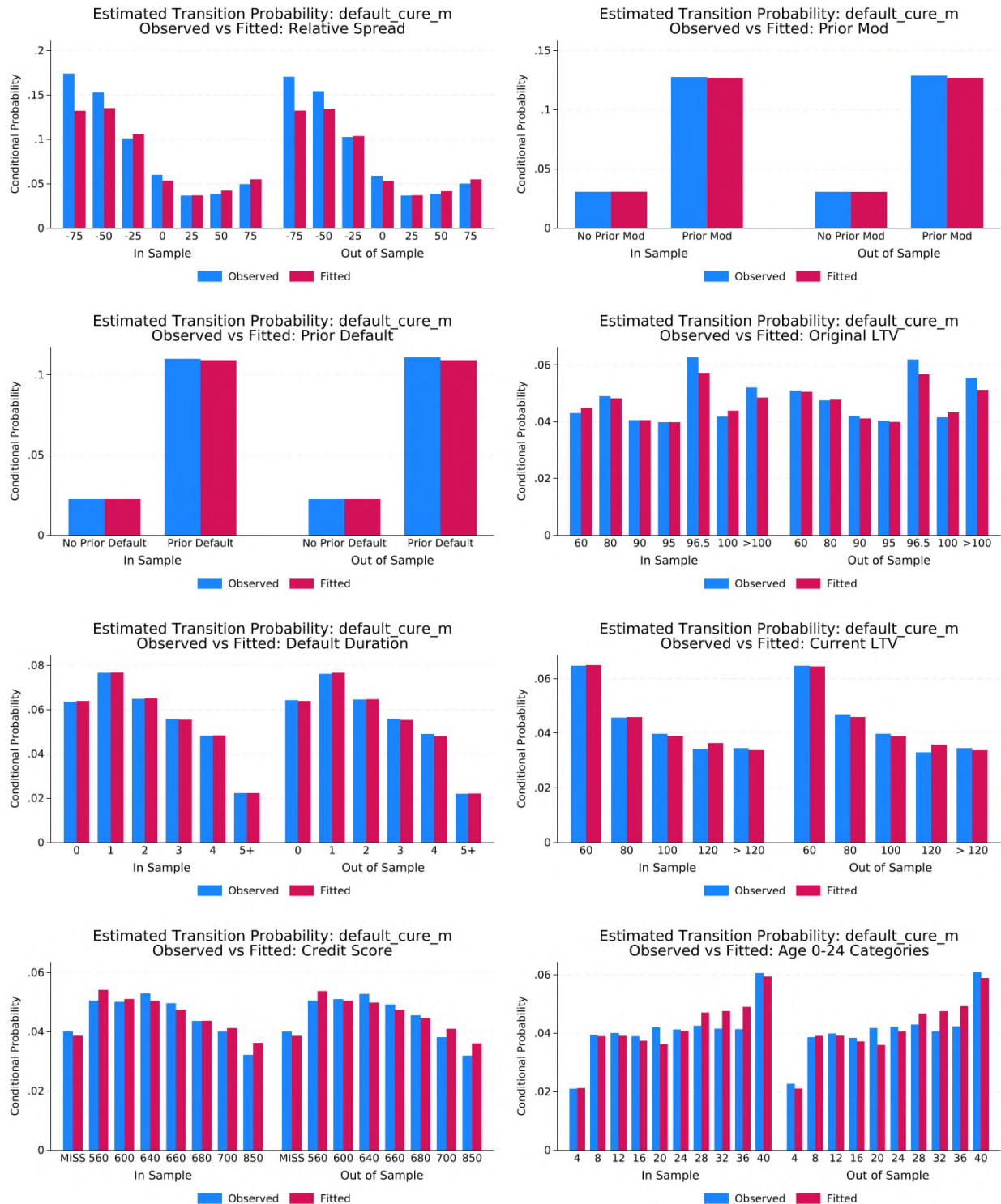
## Product 4 - current\_prepay\_sr



## Product 4 - default\_claim

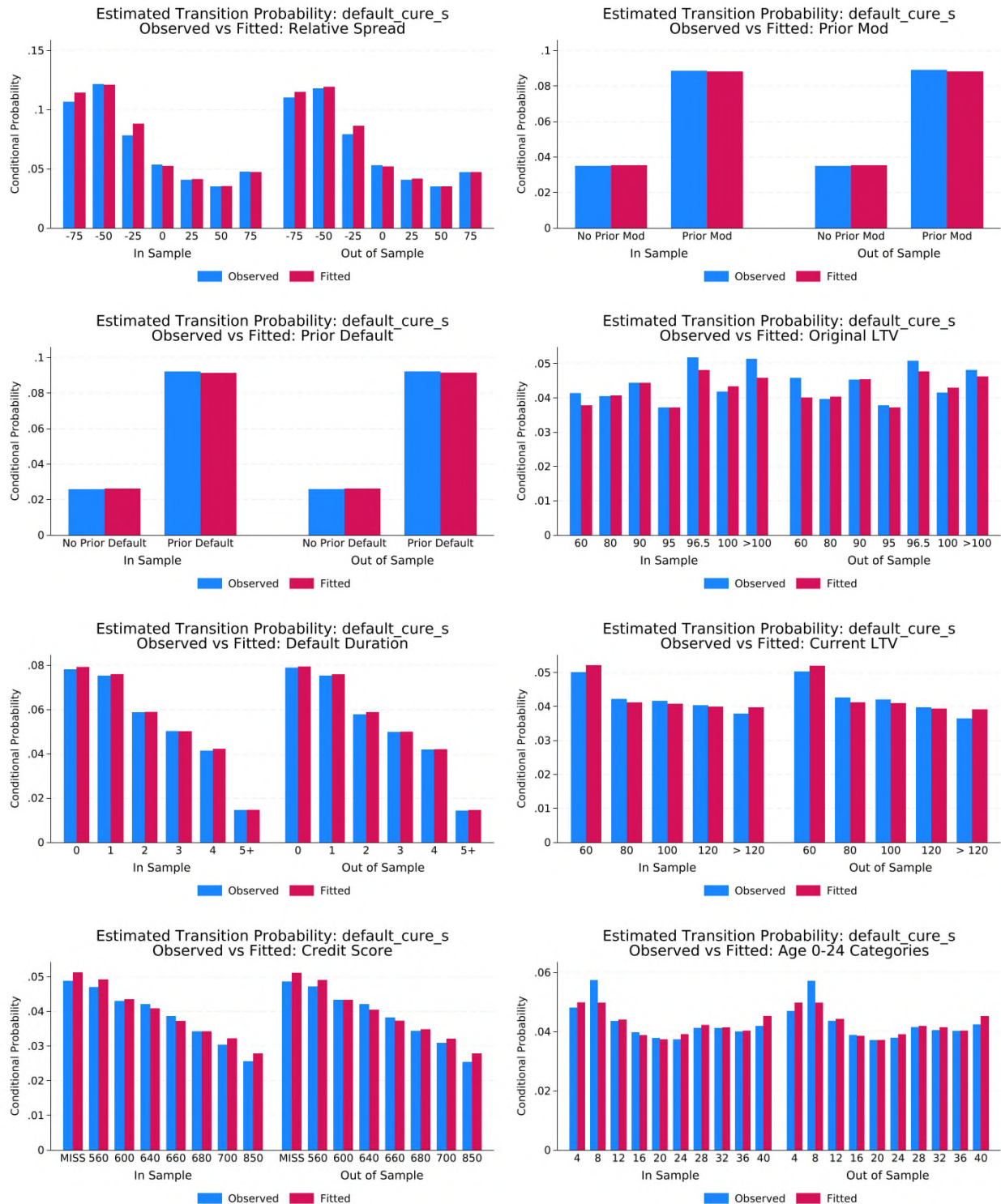


Product 4 - default\_cure\_m

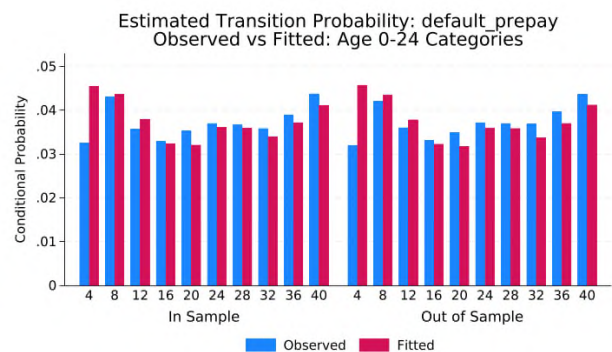
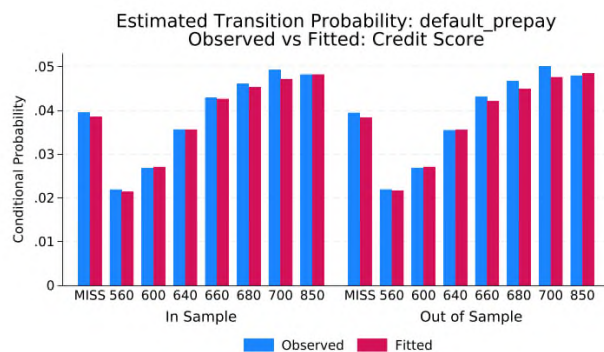
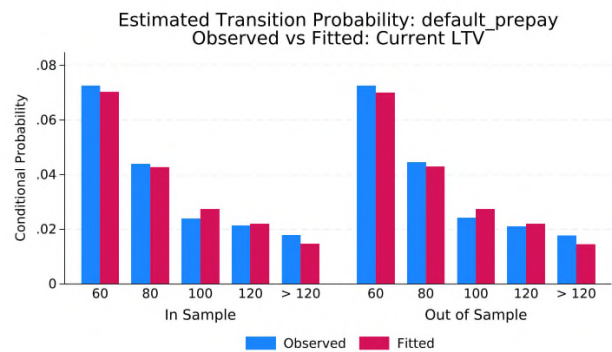
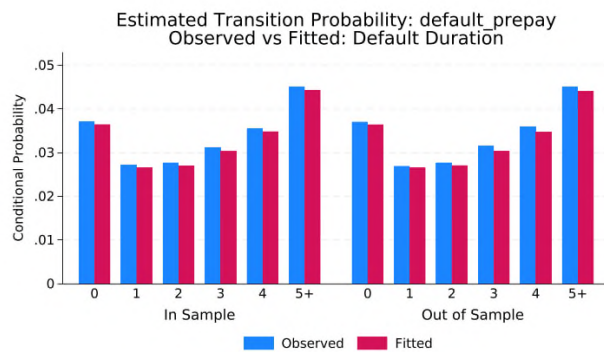
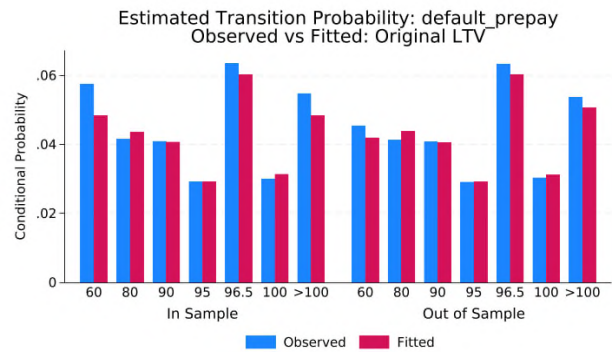
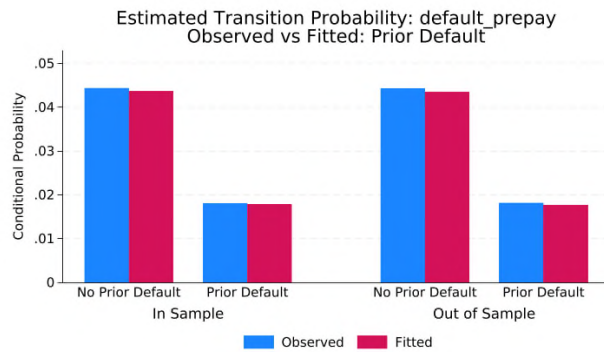
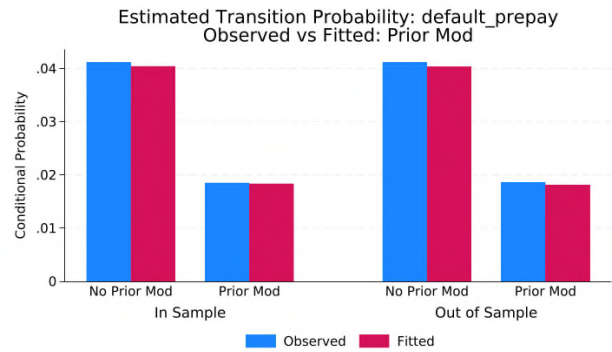
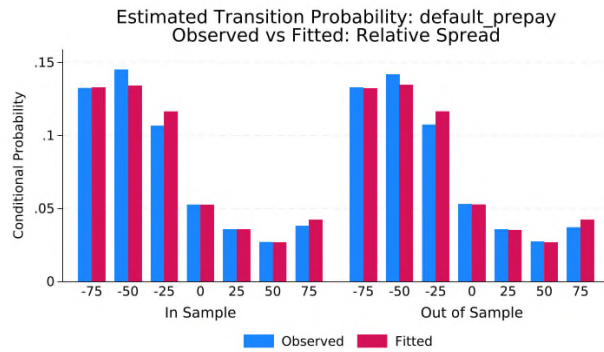




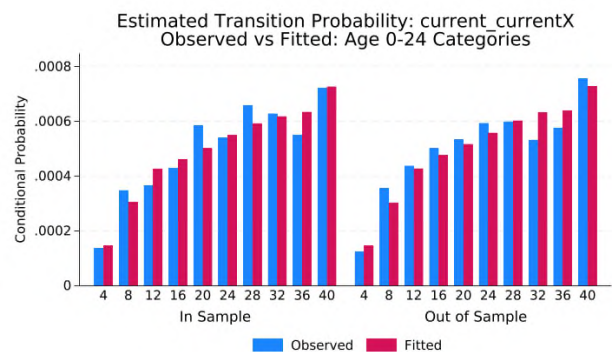
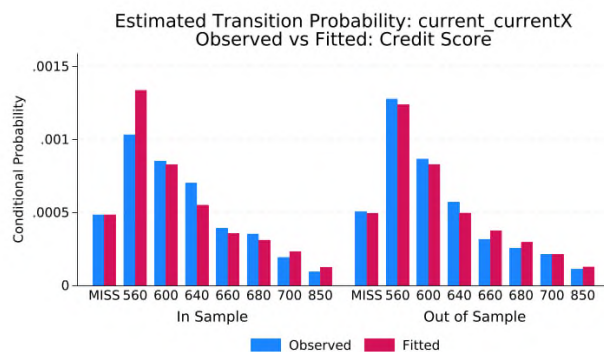
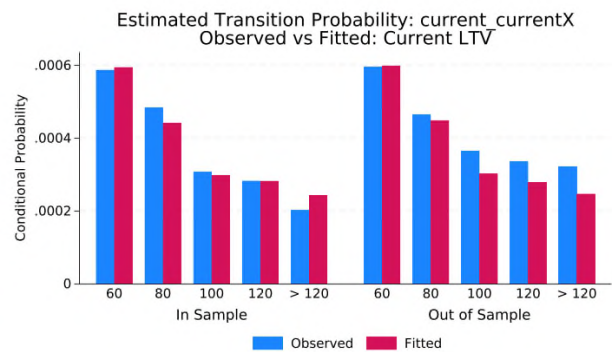
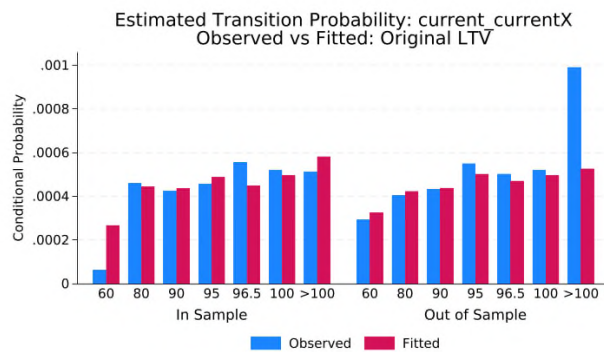
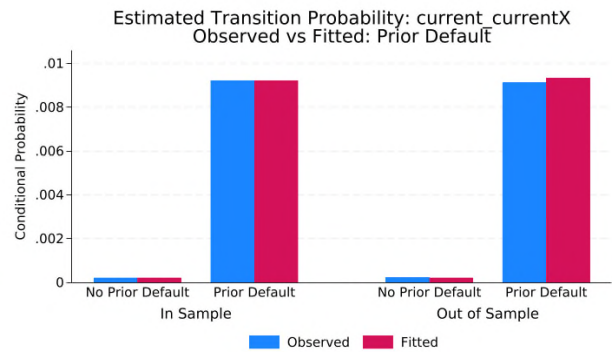
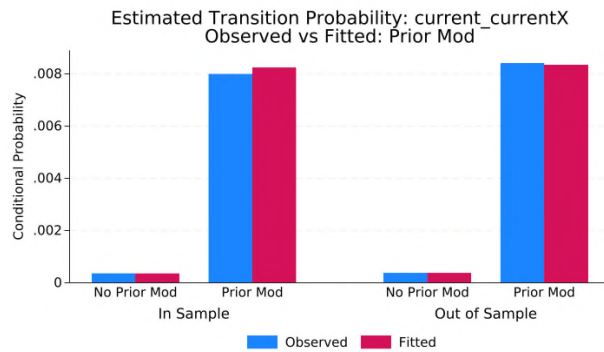
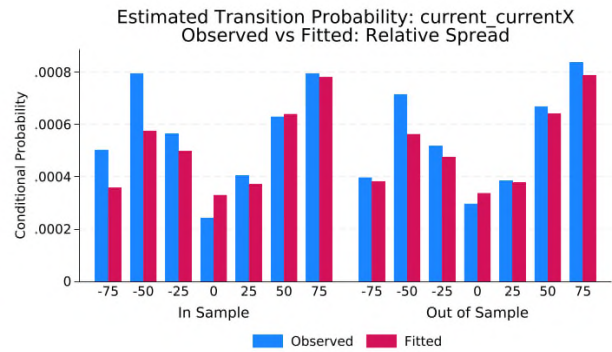
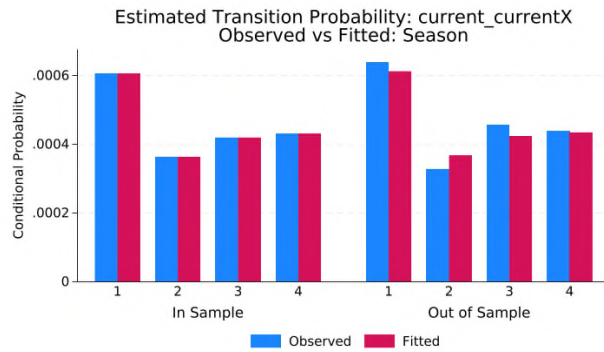
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## Product 4 - default\_prepay

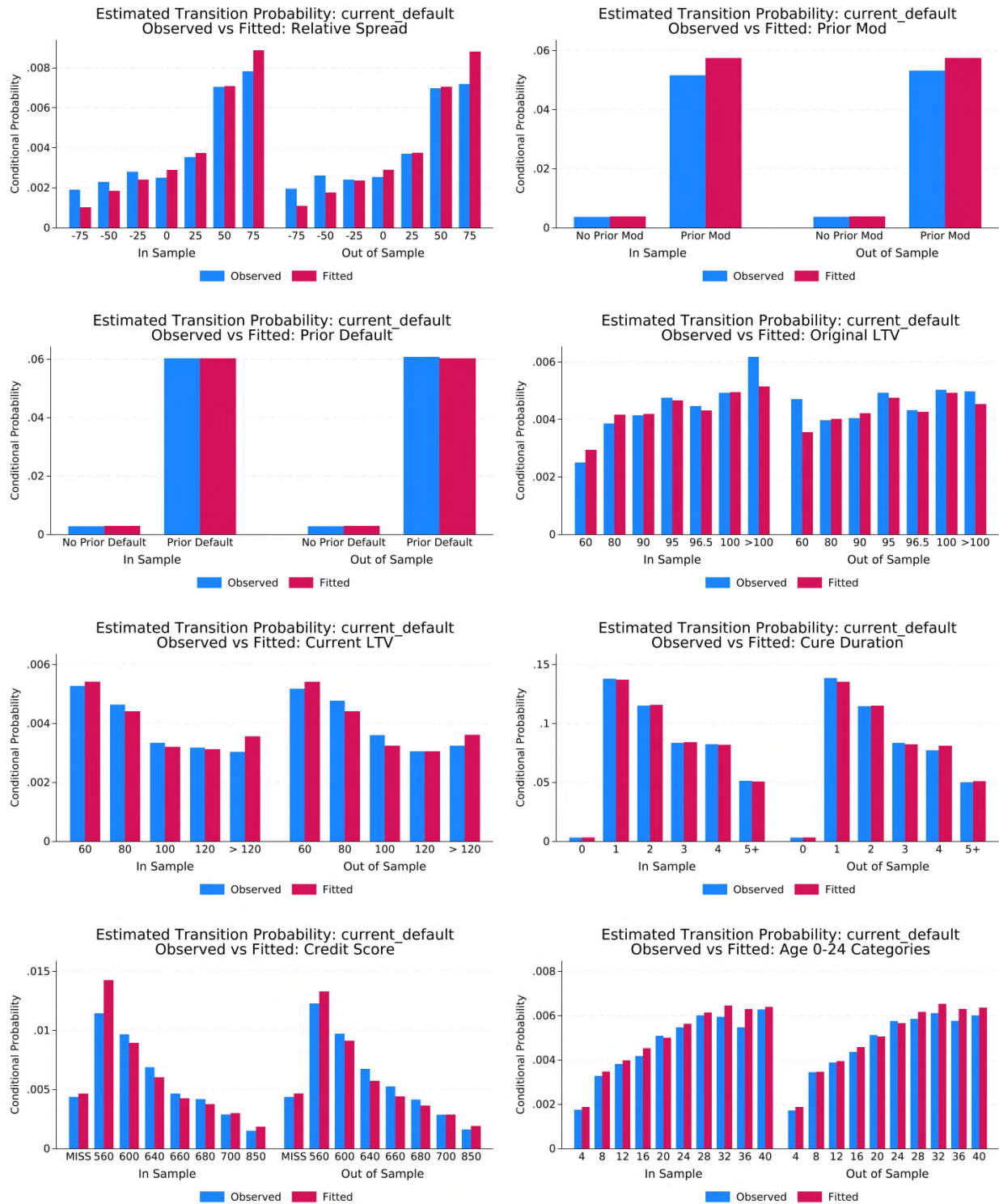


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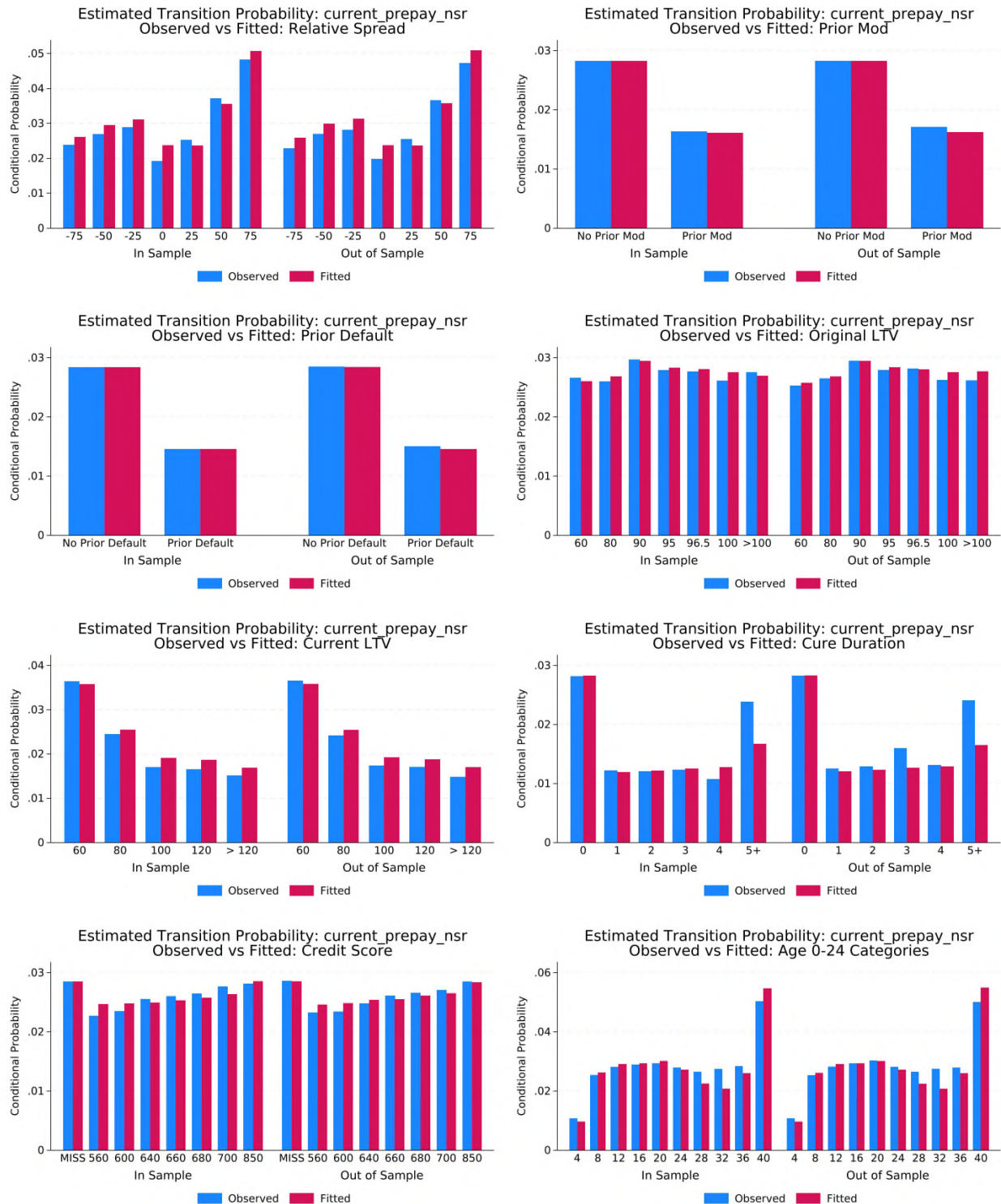




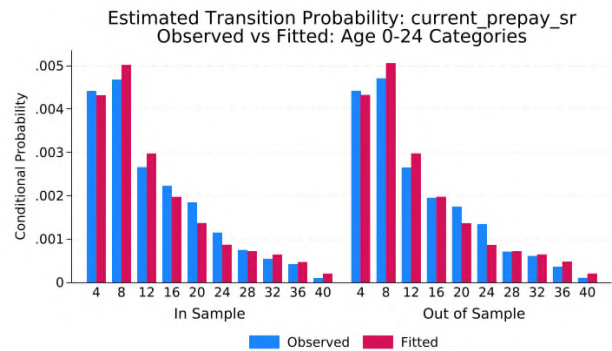
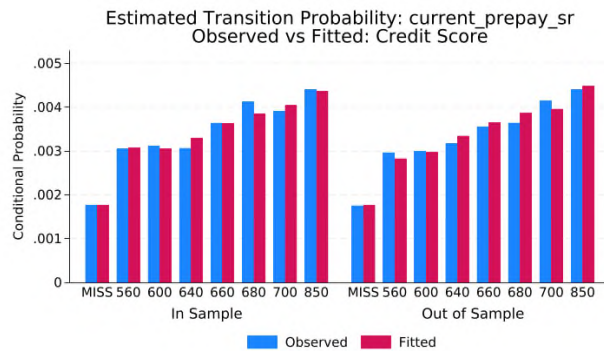
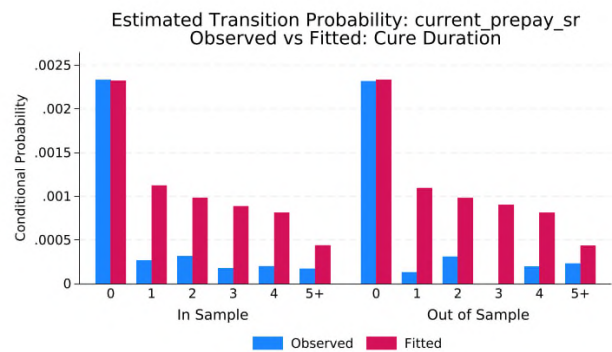
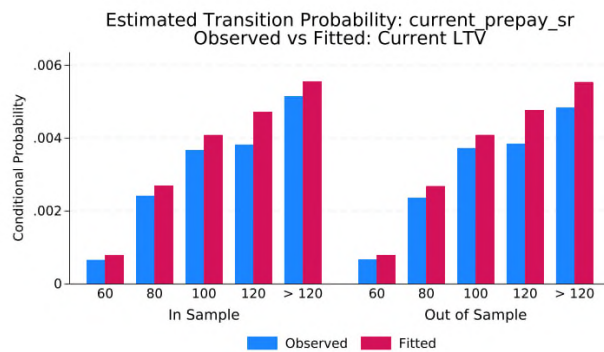
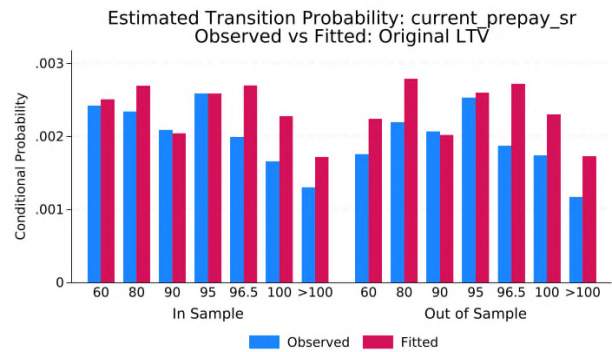
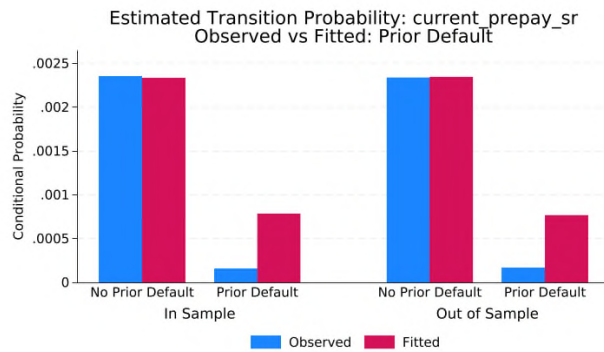
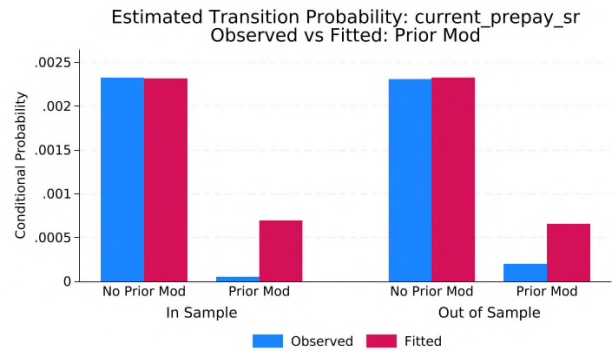
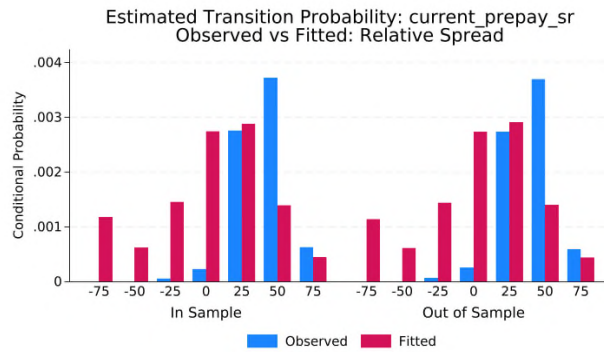
## Product 5 - current\_default



## Product 5 - current\_prepay\_nsr

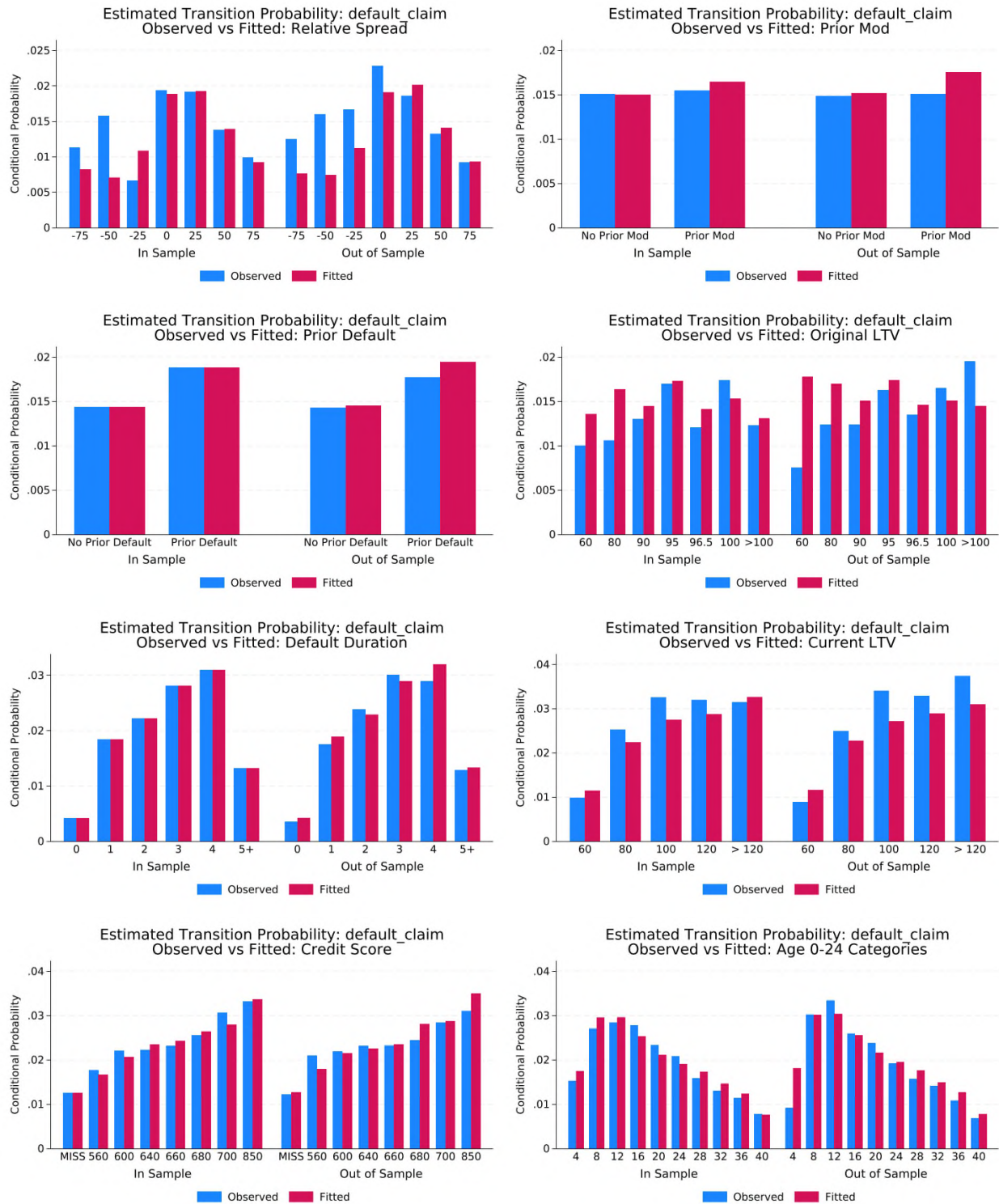


## Product 5 - current\_prepay\_sr

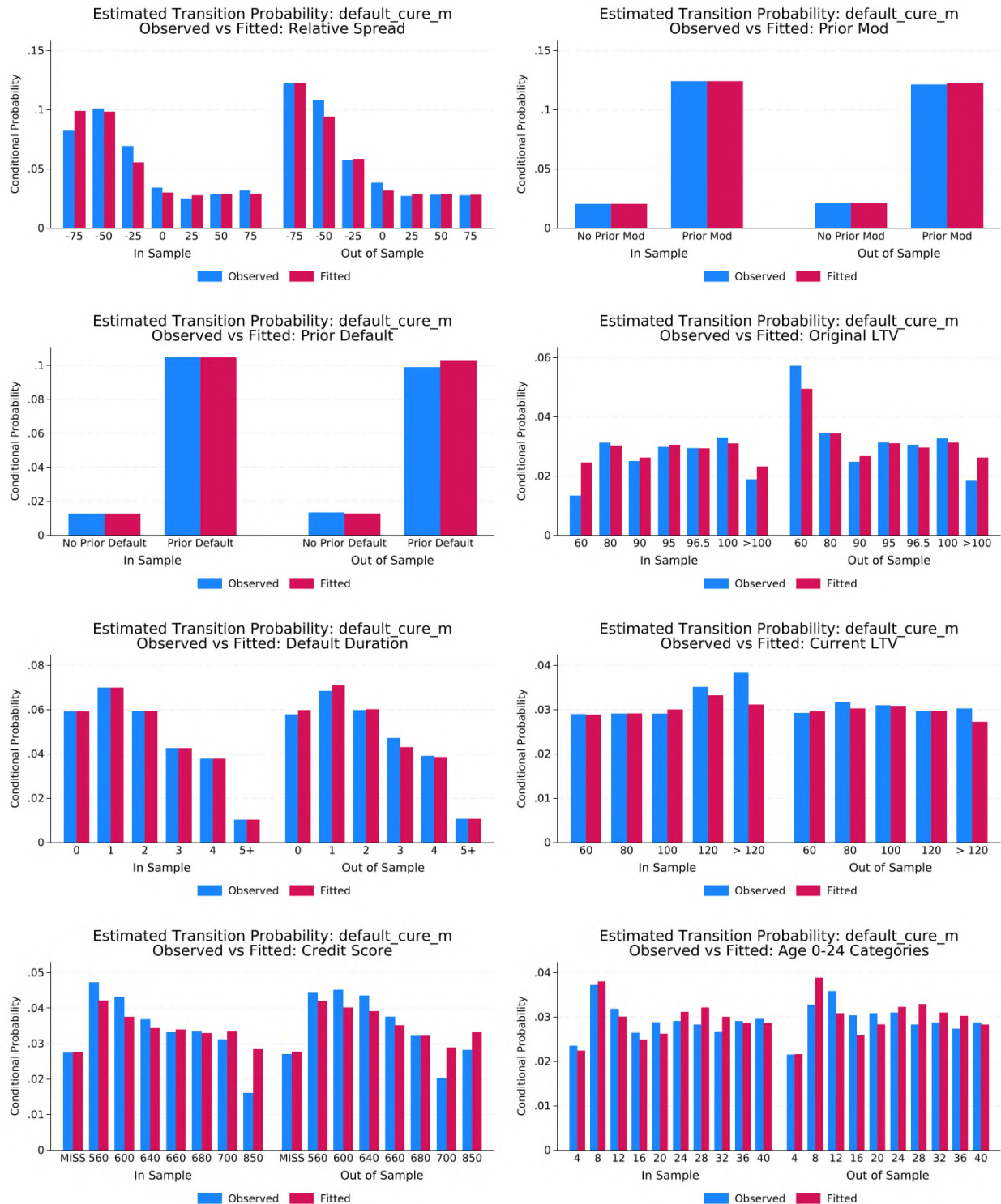




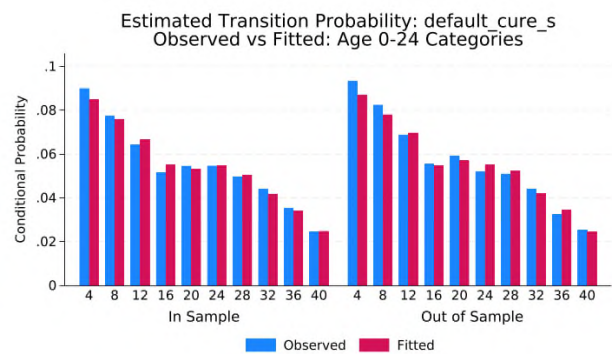
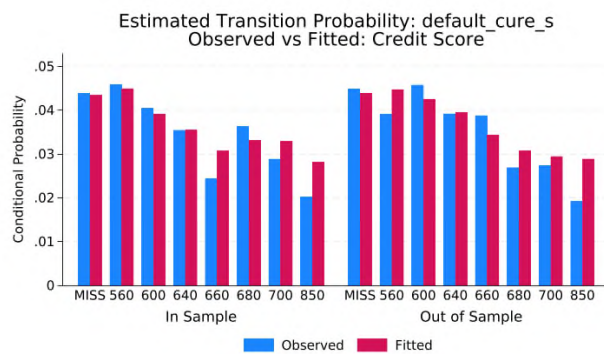
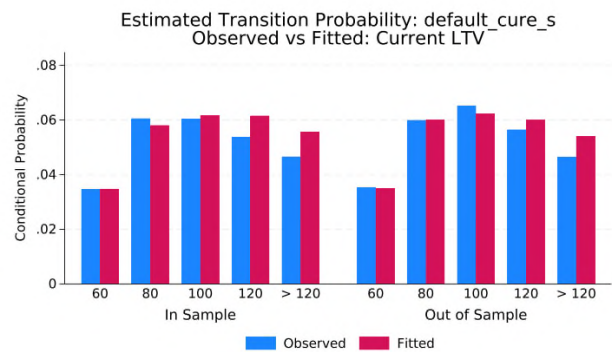
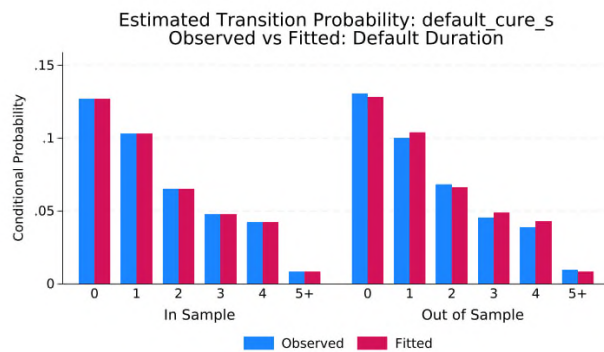
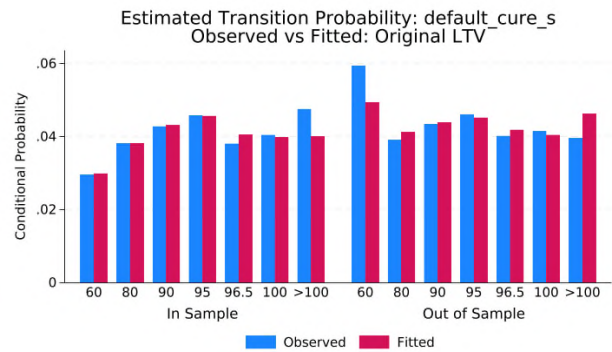
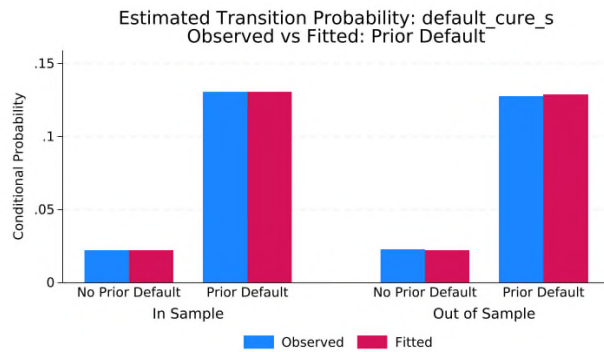
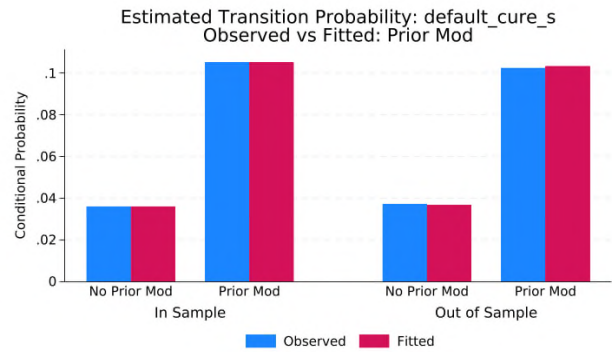
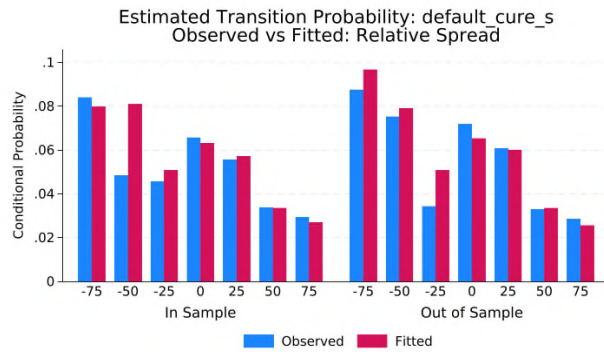
## Product 5 - default\_claim



## Product 5 - default\_cure\_m

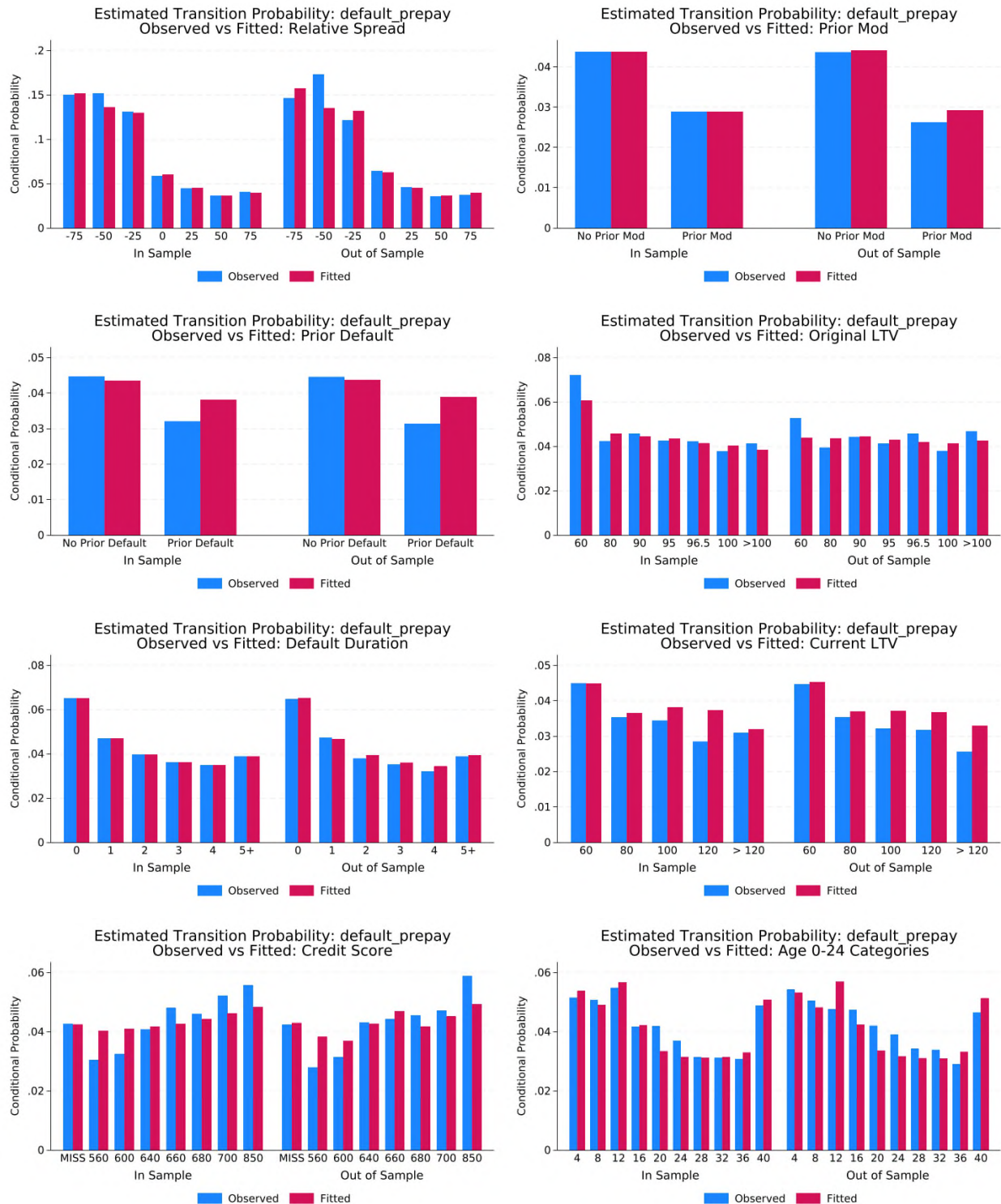


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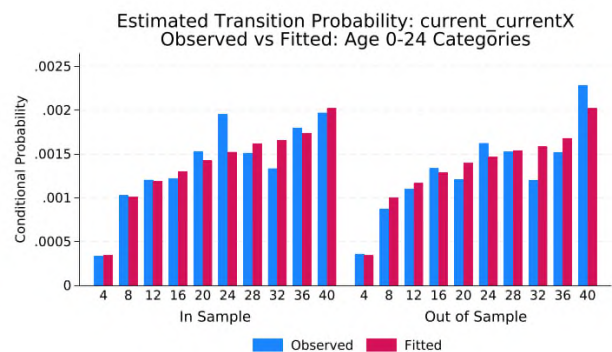
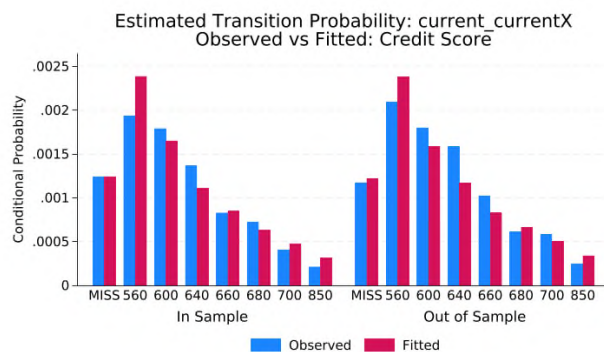
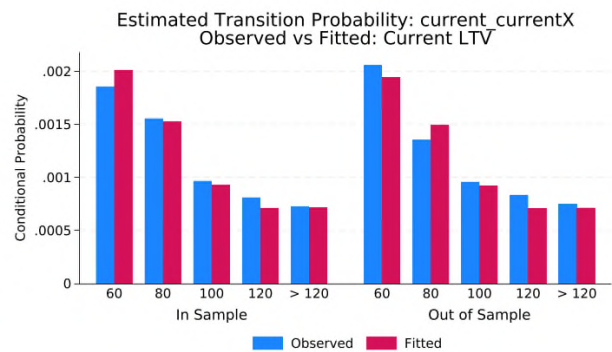
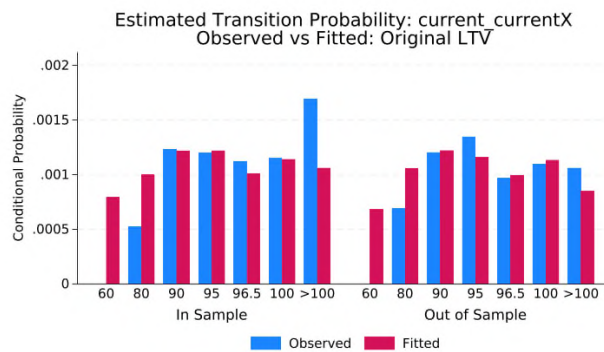
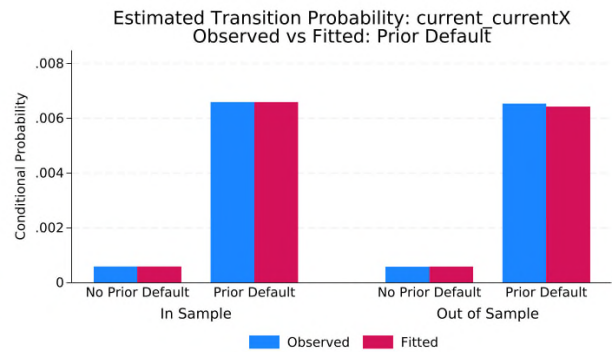
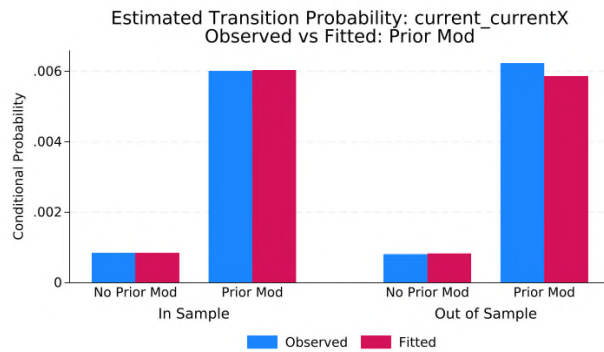
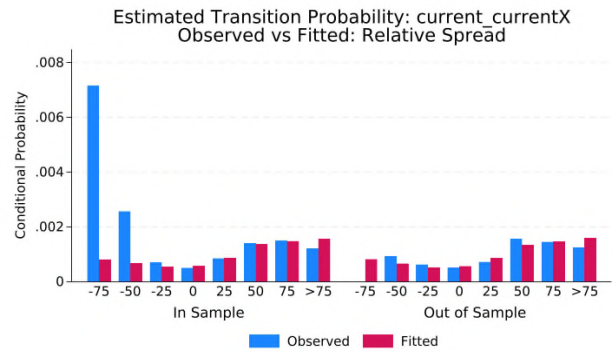
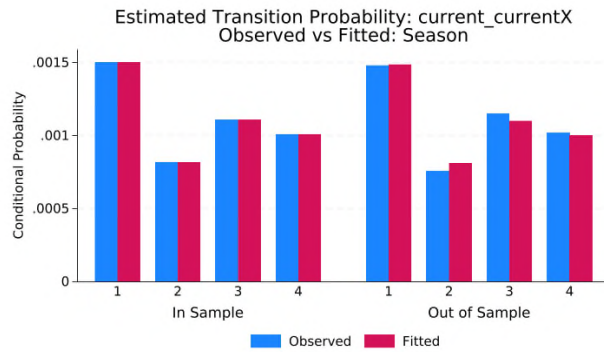




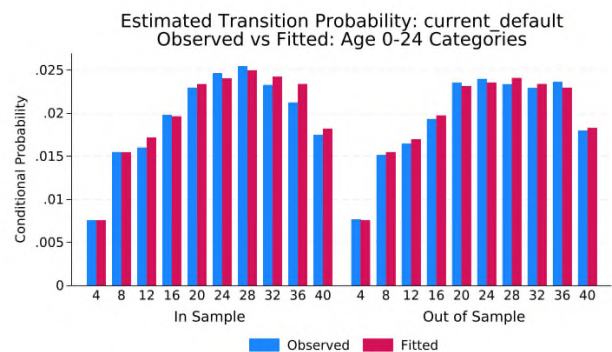
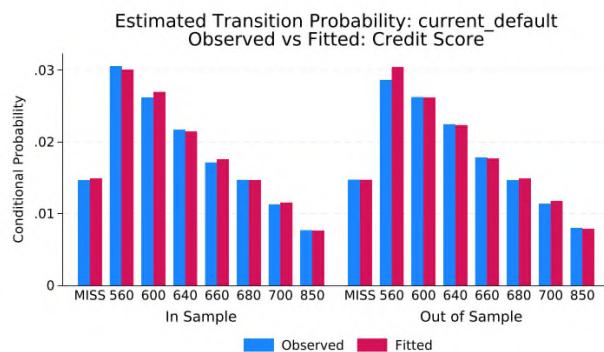
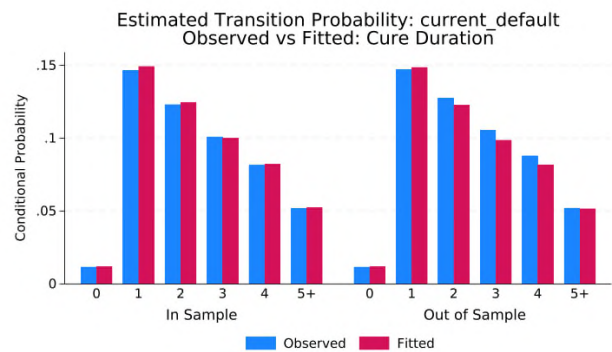
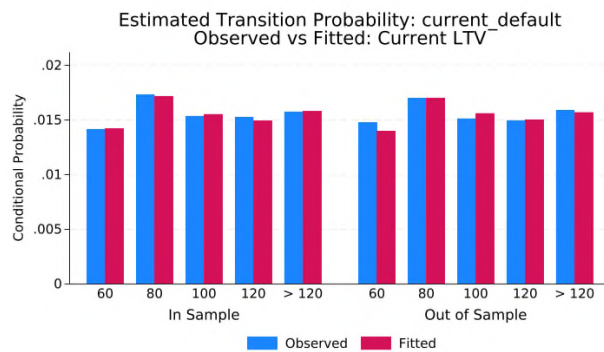
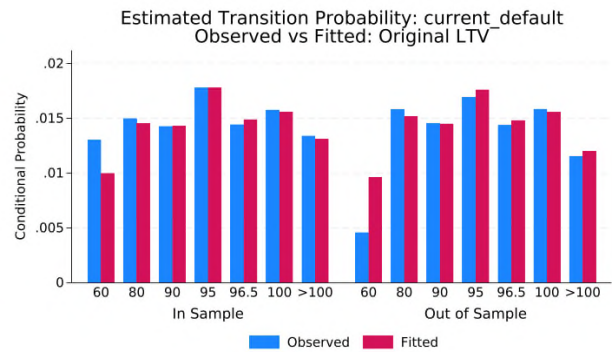
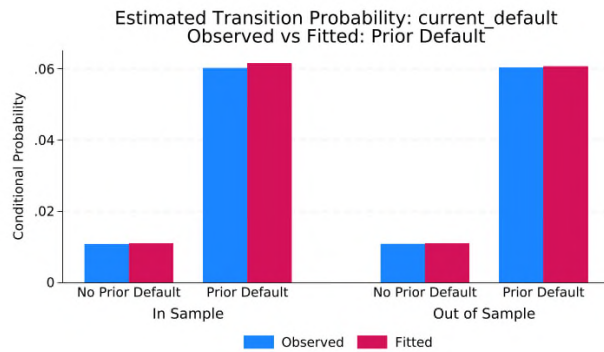
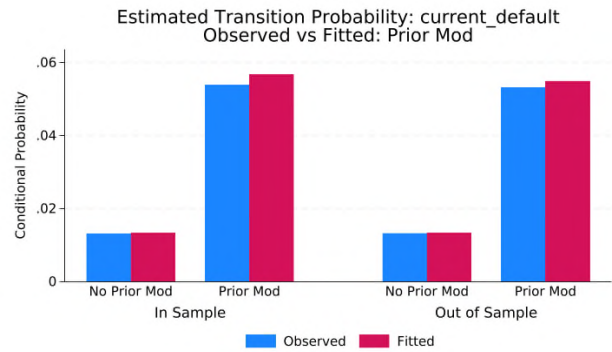
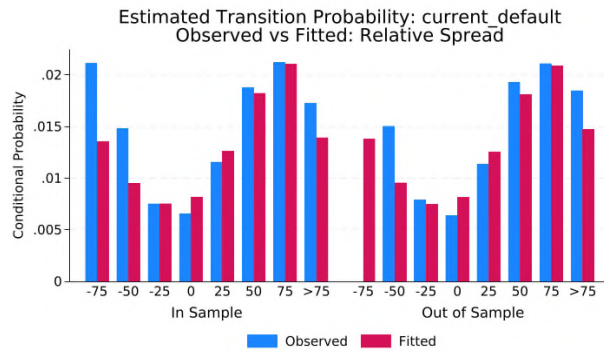
## Product 5 - default\_prepay



## Product 6 - current\_currentX

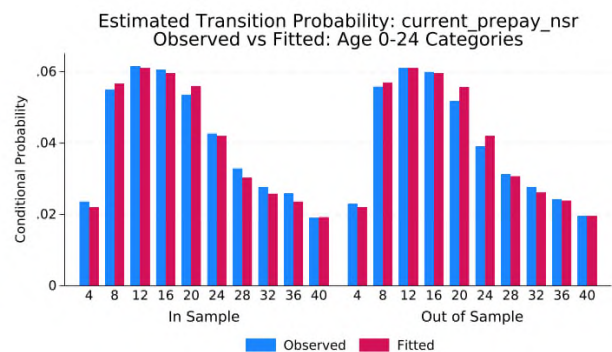
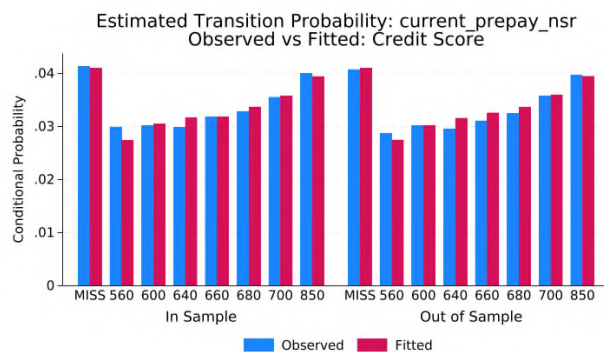
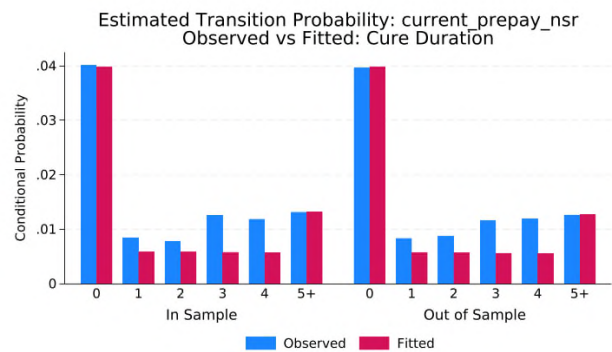
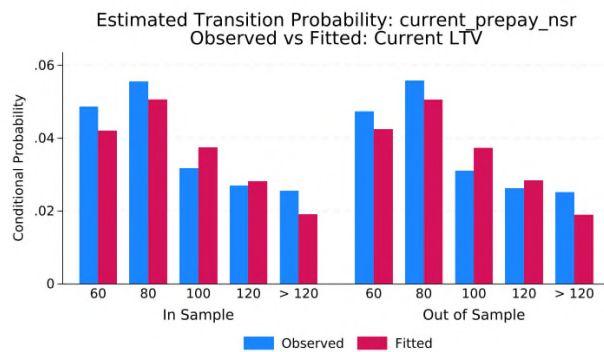
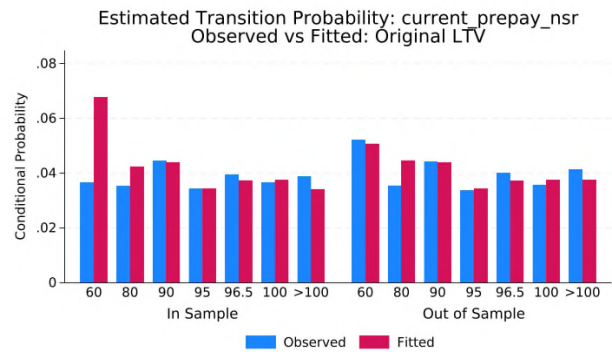
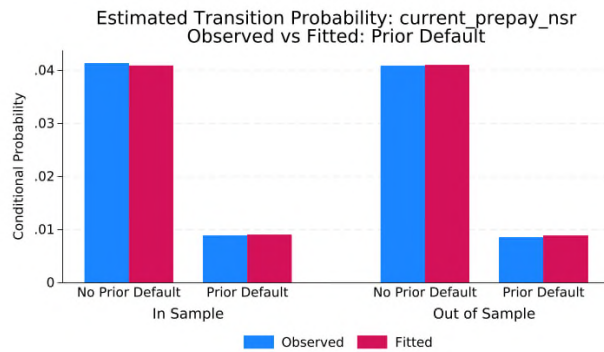
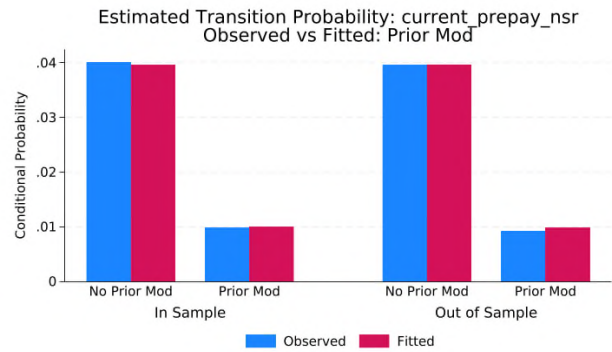
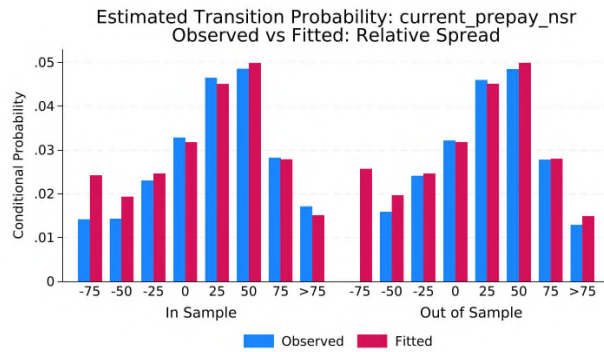


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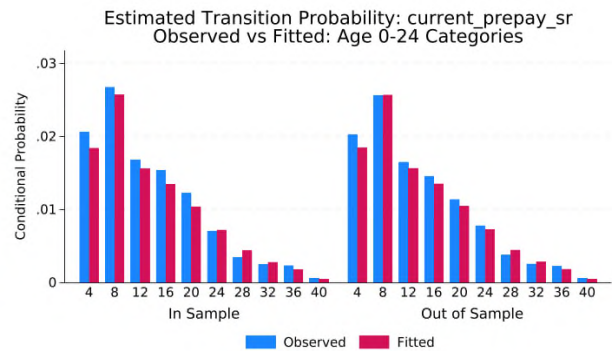
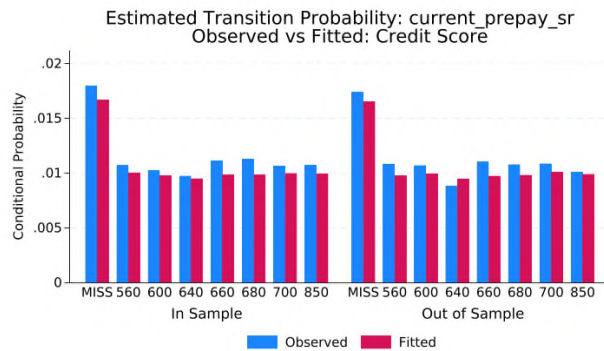
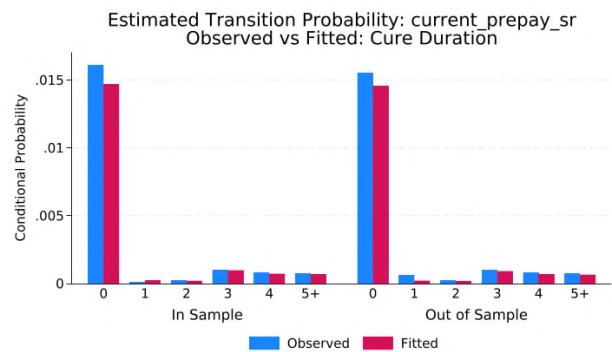
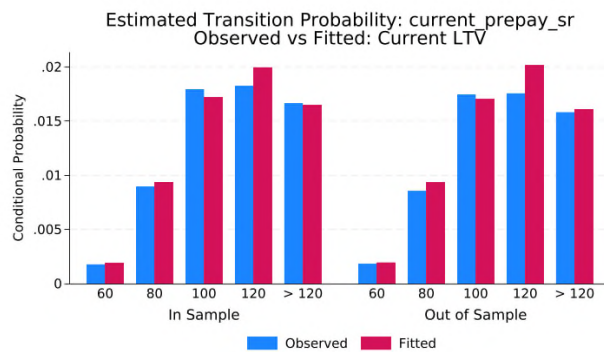
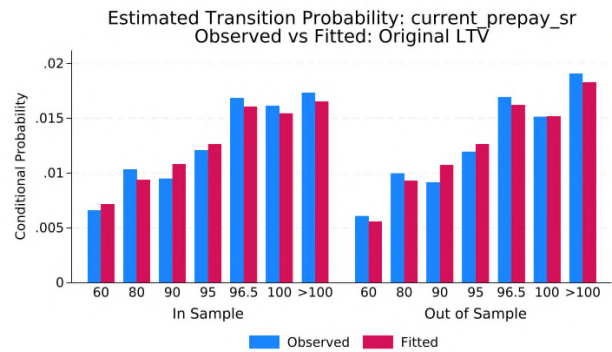
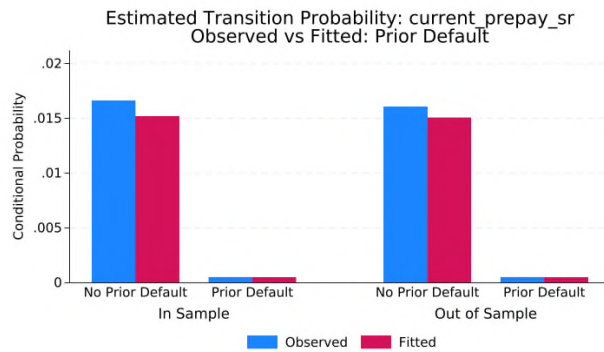
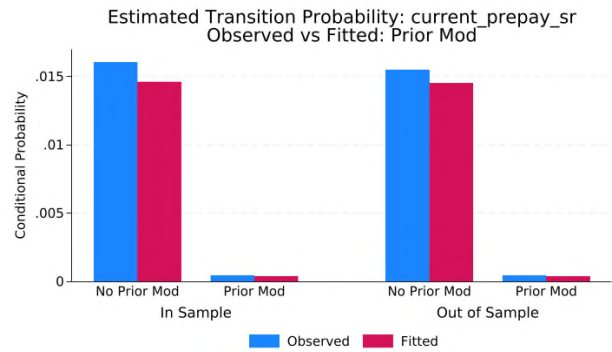
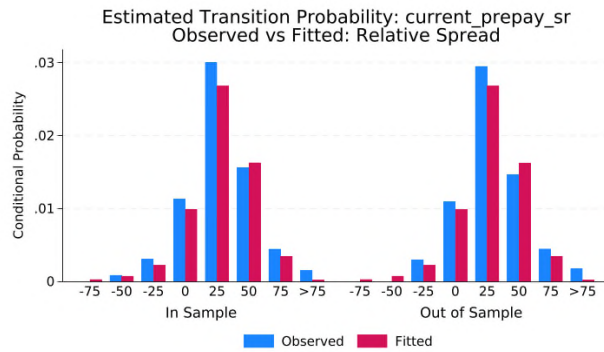




## Product 6 - current\_prepay\_nsr

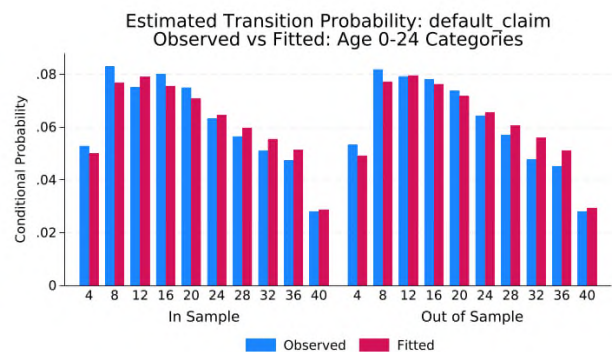
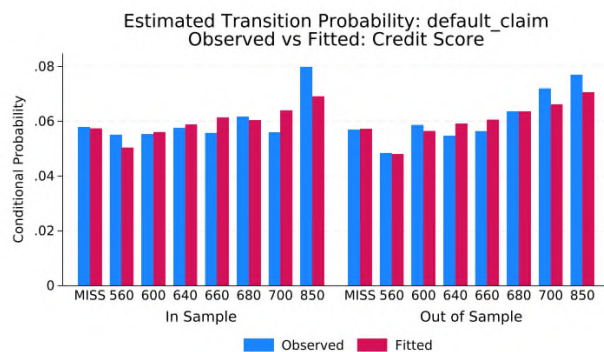
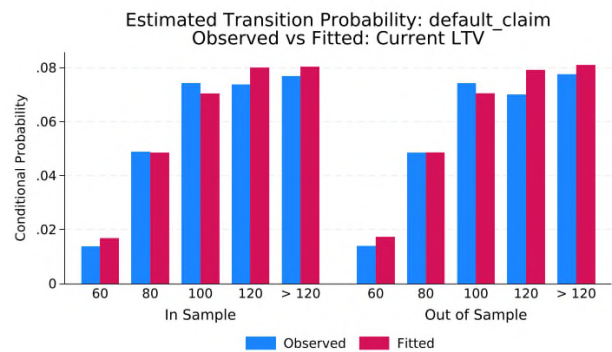
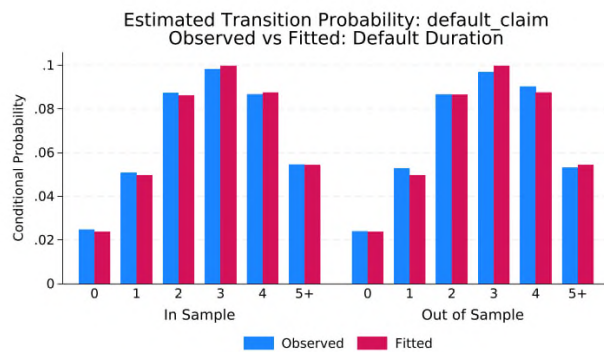
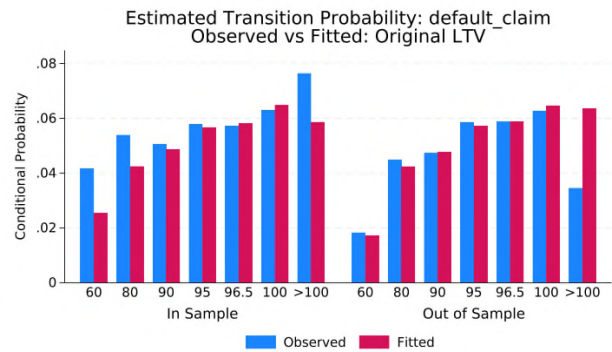
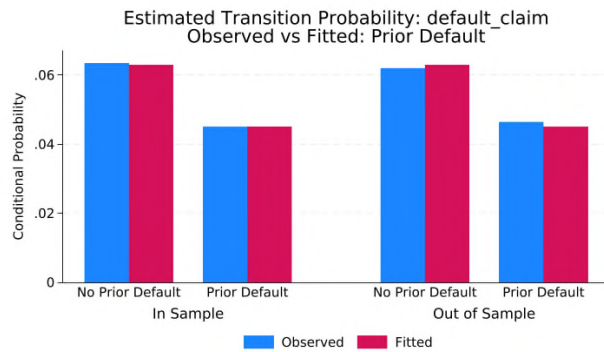
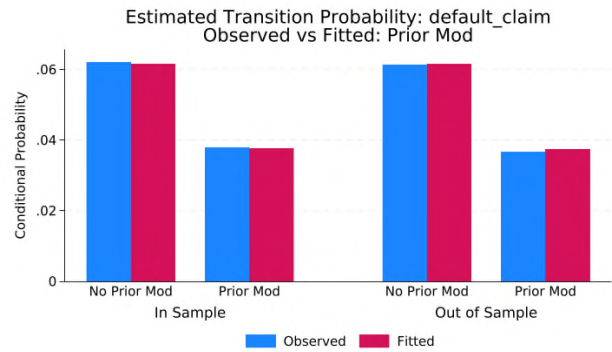
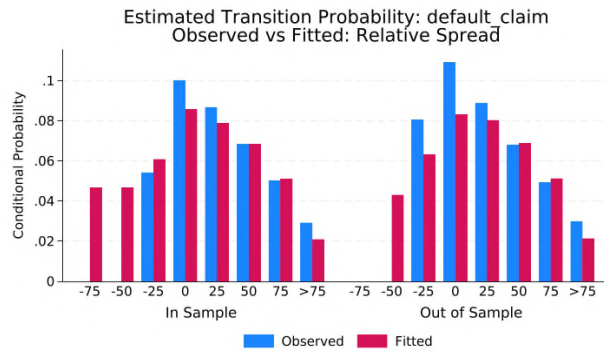


## Product 6 - current\_prepay\_sr

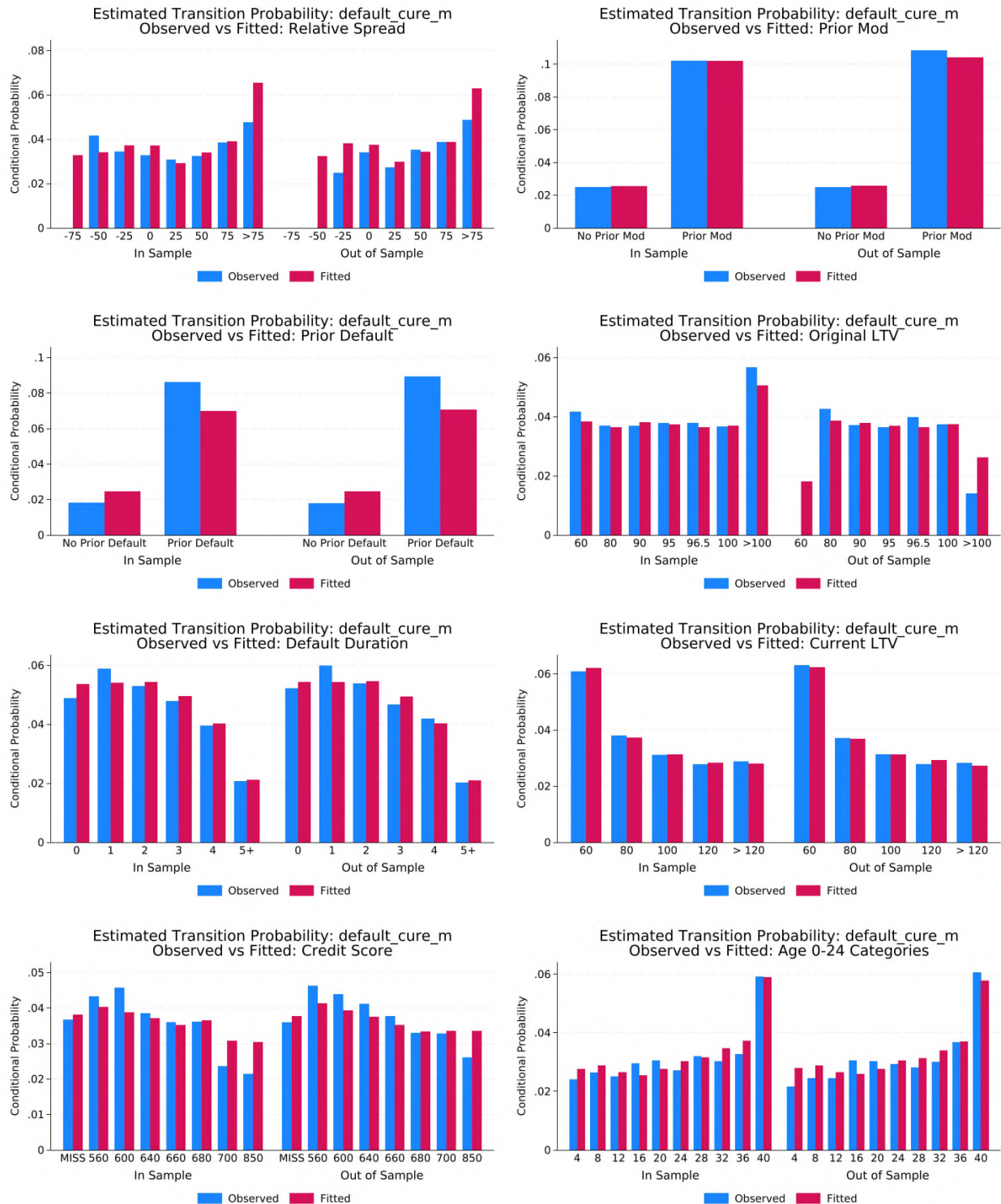




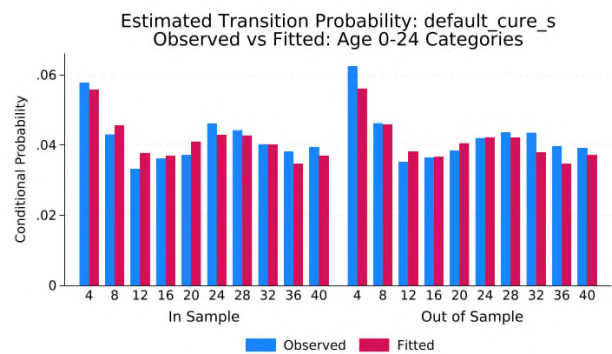
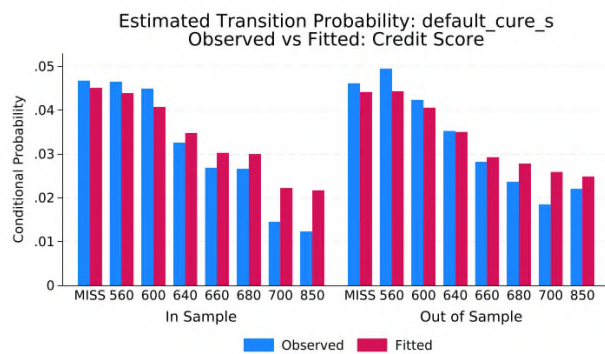
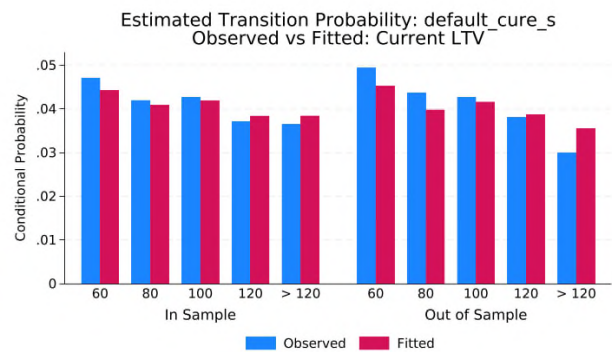
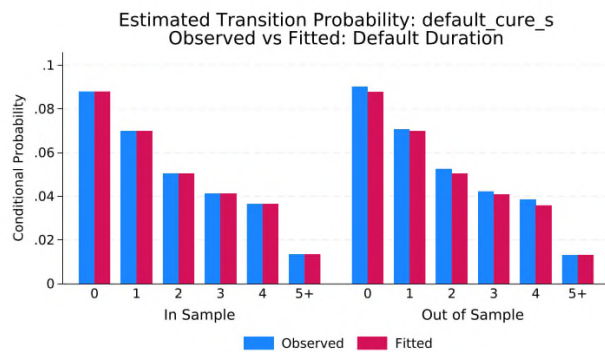
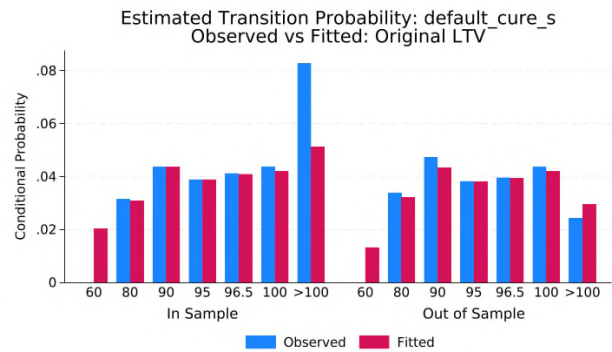
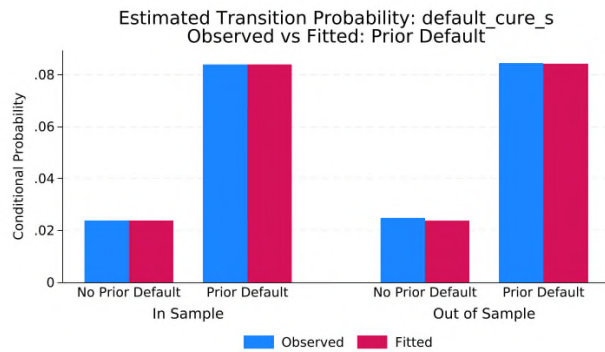
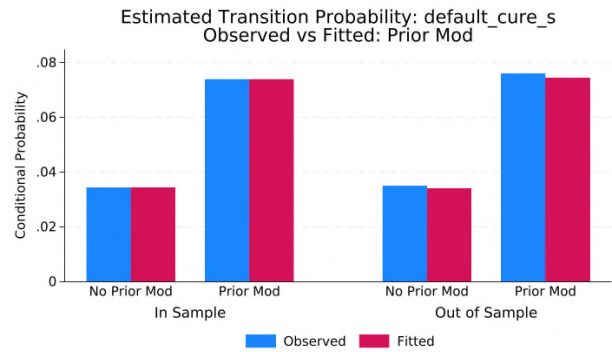
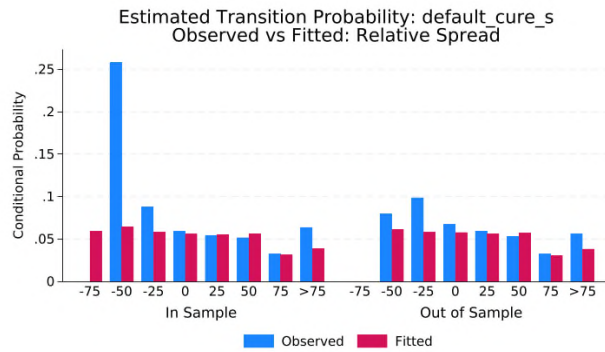
## Product 6 - default\_claim



Product 6 - default\_cure\_m

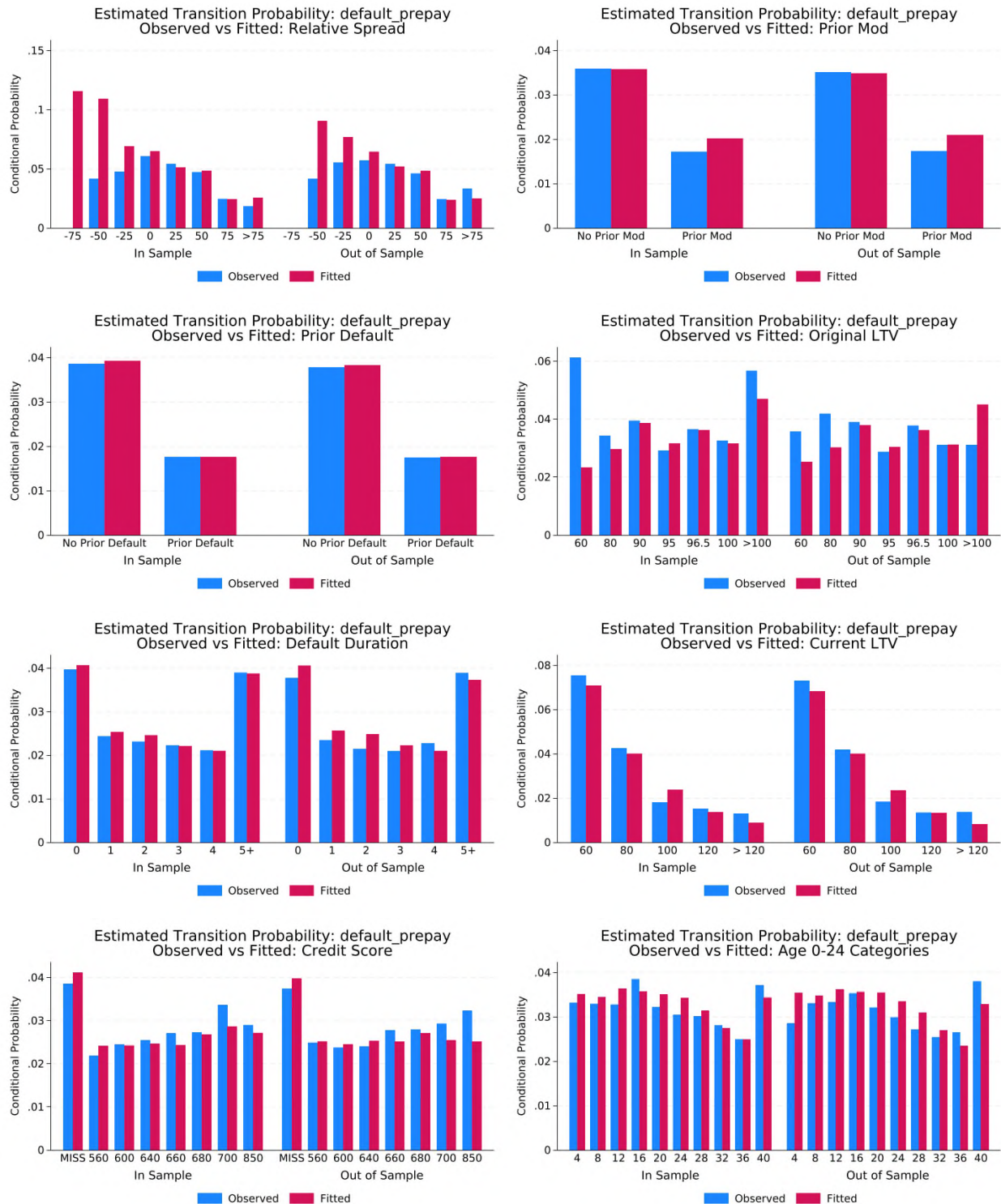


## Product 6 - default\_cure\_s





## Product 6 - default\_prepay



## Appendix C. Loan Performance Projections

### C1. General Approach to Loan Termination Projections

#### C1.1. Loan Status Transitions Modeled

Econometric models are estimated for the following transitions:

|                    |                                                     |
|--------------------|-----------------------------------------------------|
| current_default    | 90-day default event from current status            |
| current_prepay_nsr | Prepayment termination non-SR                       |
| current_prepay_sr  | Prepayment termination as SR                        |
| current_currentX   | Default and self-cure within the same quarter       |
| default_current_s  | Self-cure from default status                       |
| default_current_m  | Mod-cure from default status                        |
| default_prepay     | Prepayment termination from default status (non-SR) |
| default_claim      | Claim termination                                   |

There are two additional “transitions” corresponding to current loans that remain in current status and loans in default episodes that remain in default status. We list these for completeness but note that no estimation is undertaken since these probabilities are derived as the complement to the other probabilities for the same initial status.

|                 |                                                                           |
|-----------------|---------------------------------------------------------------------------|
| current_current | Not estimated. Derived as a complement of other current_ * probabilities. |
| default_default | Not estimated. Derived as a complement of other default_ * probabilities. |

A loan is either active in current or default status or terminated as a prepayment or claim. These are the outcomes that primarily determine future cash flows and the economic net worth of the MMI Fund. In addition, certain transitions between default and current status may have additional cash flow implications associated with partial claims, which occur when defaults are cured via loan modification, or mod-cures and FHA reimburses lenders for any losses. These contrast with self-cures, where there are no cash flow implications for the MMI Fund when the loan again becomes current.

We also distinguish two types of prepayment events from current status: prepayments via SR (streamline refinance), and other non-SR prepayments. While the occurrence of these events has similar cash flow implications for the current portfolio (termination of insurance premiums and elimination of future risk of claim), they respond differently to economic factors and vary in their



timing, warranting treatment as separate competing risks. We note that prepayments via SR from default status are prohibited under HUD regulations for SR originations.

Note that we have also included a transition referred to as current-to-currentX. These are transitions associated with 90-day default episodes that start and cure in the same quarter. The loan is identified in the SFDW as having entered 90-day default status during the quarter but does not remain in default status until the start of the next quarter. In this case, the loan would be considered to have had a prior default and a self-cure, both of which would be censored when tracking quarter-to-quarter status transitions. The primary motivation for tracking these transitions is the importance of prior default experience for predicting future behavior, although there is no recorded change in loan status; by tracking them we can more completely account for path dependence in default behavior.

Once the logit probability models have been estimated on historical data, the forecast programs rebuild the data used in estimation and extend the data into the future periods for each loan, generating new values of the explanatory variables based on the forecasted values of the same economic factors used in estimation (FHFA house price indices, BLS household unemployment rates, FHLMC mortgage rates, Census median home prices, Treasury rates, and yields). The historical series is obtained from Moody's Economy.com. The baseline scenario utilized is the PEA. We also apply four alternative scenarios based on stochastic simulation models to illustrate the sensitivity of the model to other possible outcomes. The stochastic model development is described in Appendix E.

The logit probabilities are estimated controlling for age, duration of default for loans in default status, duration of cure for previously defaulted loans in status, and indicators of prior default and prior mod. This detail in estimation makes it possible to develop the forecasted probabilities required to project the survivorship of loans or their claim or prepayment termination. The survivorship calculations are probabilistic, so it is necessary to track the shares of the portfolio stratified by age, duration of default, duration of cure, and prior default and prior mod. Before those survivorship calculations can occur, we must forecast future probabilities in a form that enables us to recover this detail along with all the other explanatory variables for each loan at each age and possible duration over the forecast period. The following section introduces the approach.

## C2. Economic Scenarios

We use the baseline assumption plus four alternative stochastic simulation scenarios. The following four alternative scenarios for which we report economic net worth estimates are:

- Optimistic Upside Scenario in Simulation, the path that is most favorable of the five selected paths to the MMI Fund.
- Moderate Upside Scenario in Simulation, the path that is moderately favorable to the MMI Fund.

- Moderate Downside Scenario in Simulation, the path that is moderately unfavorable to the MMI Fund.
- Pessimistic Downside Scenario in Simulation, the path that is most unfavorable of the five selected paths to the MMI Fund.

### C3. Future Default / Cure Probabilities by Duration and Prior Default and Prior Mod Status

When projecting data and loan performance into the future we generate probabilities that can be applied to all possible future loan situations defined in terms of initial loan status (current or default), prior default, prior modification, duration of default, duration of cure, and occurrence of claim or prepayment. This requires that we compute probabilities across all relevant durations of default or cure and simultaneously account for prior default and prior mod status.

To illustrate, consider the probabilities for current-to-default transitions covering the three possible scenarios: (1) no prior default or prior mod; (2) prior default and self-cure; and (3) prior default and prior mod. We will label these probabilities as follows:

- (1) prob\_current\_default\_N (corresponds to prior\_default=0 and prior\_mod=0)
- (2) prob\_current\_default\_S (corresponds to prior\_default=1 and prior\_mod=0)
- (3) prob\_current\_default\_M (corresponds to prior\_default=1 and prior\_mod=1)

The estimation program automatically saves the fitted parameters of each transition model to a separate file and recalls these when generating forecasts. The estimated parameters are used to recompute the linear “regression” function component of the non-linear logit probabilities of the form  $X*b$ , where  $X$  is the matrix of explanatory variables and  $b$  is the coefficient vector. We note that the regression functions  $X*b_N$ ,  $X*b_S$ , and  $X*b_M$  for each of the probabilities above will differ only about the values of prior\_default and prior\_mod, as all other variables of  $X$  will be identical at a given age and duration of default for a particular loan. This implies that the regression function  $X*b_S$  for prob\_current\_default\_S can be computed from  $X*b_M$  by simply subtracting the coefficient for prior\_mod, thus implicitly changing prior\_mod=1 to prior\_mod=0. Similar calculations can be applied to all other transition types as well.

In practice this is achieved by the following steps:

- (1) add additional records at each future age corresponding to each possible duration 0, 1, ..., D and set prior\_default=1 and prior\_mod=1 for all these future loan records;
- (2) compute  $X*b_M$  and prob\_current\_default\_M at each duration 0, 1, ..., D ;
- (3) compute  $X*b_S$  by subtracting the coefficient for prior\_mod=1 from  $X*b_M$  and use to compute prob\_current\_default\_S at each duration 0, 1, ..., D;
- (4) compute  $X*b_N$  by subtracting the coefficient for prior\_default=1 from  $X*b_S$  and use to compute prob\_current\_default\_N at each duration 0, 1, ..., D .

This results in new data columns for each of the three probabilities at each future age and hypothetical duration. The duration-specific synthetic loan records created for each future age of the loan simultaneously utilize identical forecasted values for all explanatory variables other than the relevant duration value. The updated forecast data are then saved for input into subsequent survivor programs that will select and apply the loan-status and duration-specific probabilities to the appropriate survivor totals to evolve the portfolio further into future periods.

## C4. Actuarial Projections

### C4.1. Further Stratification of Transition Probabilities to Compute Survivorship

Given these basic events, the timing and duration of changes in loan status depend on the path that each loan takes on its way to prepayment or claim. Much of this path dependence can be captured by tracking the duration of default for defaulted loans, whether a loan has a prior default, whether a defaulted loan cures through a loan modification or self-cures, the duration of cure for cured loans, and whether a defaulted or cured loan has a prior modification.

The more detailed and specific transition probabilities that are needed for the actuarial calculations for each event type described above are listed below, where duration of default takes values 0,1,..., D; duration of cure takes values 0, 1, 2, ..., C; “N” refers to having had no prior default or prior modification; “S” refers to having a prior default that was self-cured, but no prior modification; “M” refers to having had a prior default that mod-cured; lower-case “s” refers to self-cure transitions; and lower-case “m” refers to mod-cure transitions.

Loan transitions from current status are duration-dependent only if there was a prior default that has self-cured (S) or mod-cured (M). Duration of cure is indicated by 0, 1, 2, ..., C. The values of C and D are set to the same maximum value. During data construction and estimation, observed durations higher than C or D are given maximum value so the maximum duration represents duration  $\geq$  C or D quarters. At present, values of C=D=5 quarters have been applied, in part because observed transition rates seem to level off by that point, and because the data become thinner so estimating beyond that point is both materially unimportant and unreliable.

### C4.2. Survivorship Probabilities

#### current-to-default

|               |                                                        |
|---------------|--------------------------------------------------------|
| pr_cur_def_N  | no duration dependence, no prior default, no prior mod |
| pr_cur0_def_S | duration cure 0, prior default, no prior mod           |
| pr_cur0_def_M | duration cure 0, prior default, prior mod              |
| pr_cur1_def_S | duration cure 1, prior default, no prior mod           |
| pr_cur1_def_M | duration cure 1, prior default, prior mod              |

|  
pr\_curC\_def\_S                      duration cure C, prior default, no prior mod  
pr\_curC\_def\_M                      duration cure C, prior default, prior mod

current-to-prepay (non-SR)

pr\_cur\_pre\_nsr\_N  
pr\_cur0\_pre\_nsr\_S  
pr\_cur0\_pre\_nsr\_M  
pr\_cur1\_pre\_nsr\_S  
pr\_cur1\_pre\_nsr\_M  
|  
pr\_curC\_pre\_nsr\_S  
pr\_curC\_pre\_nsr\_M

current-to-prepay (SR)

pr\_cur\_pre\_sr\_N  
pr\_cur0\_pre\_sr\_S  
pr\_cur0\_pre\_sr\_M  
pr\_cur1\_pre\_sr\_S  
pr\_cur1\_pre\_sr\_M  
|  
pr\_curC\_pre\_sr\_S  
pr\_curC\_pre\_sr\_M

current-to-currentX

pr\_cur\_curX\_N  
pr\_cur0\_curX\_S

pr\_cur0\_curX\_M

pr\_cur1\_curX\_S

pr\_cur1\_curX\_M

|

pr\_curC\_curX\_S

pr\_curC\_curX\_M

default-to-current

pr\_def0\_cur\_s\_N duration default 0, no prior default, no prior modification, self-cure

pr\_def0\_cur\_s\_S duration default 0, prior default, no prior modification, self-cure

pr\_def0\_cur\_s\_M duration default 0, prior default, prior modification, self-cure

pr\_def1\_cur\_s\_N duration default 1, no prior default, no prior modification, self-cure

pr\_def1\_cur\_s\_S duration default 1, prior default, no prior modification, self-cure

pr\_def1\_cur\_s\_M duration default 1, prior default and prior modification, self-cure

|

pr\_defD\_cur\_s\_N duration default D, no prior default, no prior modification, self-cure

pr\_defD\_cur\_s\_S duration default D, prior default, no prior modification, self-cure

pr\_defD\_cur\_s\_M duration default D, prior default, prior modification, self-cure

pr\_def0\_cur\_m\_N duration default 0, no prior default, no prior modification, mod-cure

pr\_def0\_cur\_m\_S duration default 0, prior default (self-cure), no prior modification, mod-cure

pr\_def0\_cur\_m\_M duration default 0, prior default and prior modification, mod-cure

pr\_def1\_cur\_m\_N duration default 1, no prior default, no prior modification, mod-cure

pr\_def1\_cur\_m\_S duration default 1, prior default (self-cure), no prior modification, mod-cure

pr\_def1\_cur\_m\_M duration default 1, prior default and prior modification, mod-cure

|

pr\_defD\_cur\_m\_N duration default D, no prior default, no prior modification, mod-cure



pr\_defD\_cur\_m\_S      duration default D, prior default (self-cure), no prior modification, mod-cure

pr\_defD\_cur\_m\_M      duration default D, prior default and prior modification, mod-cure

default-to-prepay

pr\_def0\_pre\_N

pr\_def0\_pre\_S

pr\_def0\_pre\_M

pr\_def1\_pre\_N

pr\_def1\_pre\_S

pr\_def1\_pre\_M

⋮

pr\_defD\_pre\_N

pr\_defD\_pre\_S

pr\_defD\_pre\_M

default-to-claim

pr\_def0\_clm\_N

pr\_def0\_clm\_S

pr\_def0\_clm\_M

pr\_def1\_clm\_N

pr\_def1\_clm\_S

pr\_def1\_clm\_M

⋮

pr\_defD\_clm\_N

pr\_defD\_pre\_S

pr\_defD\_pre\_M

The future probabilities correspond to estimated transition probabilities to be applied to loans in specific loan statuses with the corresponding initial conditions regarding age, duration, and path dependence. To clarify, note that N, S, and M refer to the path dependence of a loan and along with duration comprise “initial conditions” for the next transition. Conversely, the lower-case s and m distinguish types of cure events. Thus, a loan in default may have either N, S, or M to define their prior history and still undertake either a self-cure or mod-cure to end a default episode.

There is no further updating of N, S, and M once a loan has had both a prior default and prior mod and labeled an M-type transition, and a loan may go directly from N-type to M-type since a prior mod implies a prior default. S describes loans that have only had one or more self-cures and never been modified, while M describes loans that have had at least one modification and may have had one or more prior self-cures as well. Loan modification implies third-party intervention that changes the terms of the mortgage (and potentially debt forgiven), whereas self-cure is basically “catching up” on delinquent payments. Accounting for S and M is about controlling for path dependence to improve estimation and not about the cash flow impacts of partial claims arising from loan modifications. The latter is accounted for by distinguishing between self-cure (s) and mod-cure (m) events, and both self-cures (s) and mod-cures (m) may occur to defaulted loans in any initial N, S, or M status and duration of default.

The survivor programs include the further development of the forecasted probabilities just described as a first step. The next step is to apply those probabilities to evolve loans forward from the final historical period during which actual loan statuses and durations are observed for the last time, to probabilistically allocate them to the potential future statuses and durations in the subsequent periods.

We expand the categories of loans to be projected to include initial status, duration, prior default, and mod history according to the same mnemonics used above for the probabilities. For example, default3\_S would measure total loans in a current default episode of duration 3 that have a prior default that self-cured and would be multiplied by probability pr\_def3\_def\_S to obtain default4\_S, the corresponding total for duration 4. Of course, the updating is proportional based on the probability and some of the loans in default3\_S would proceed to current status (with probability pr\_def3\_cure\_s\_S for self-cure and probability pr\_def3\_cur\_m\_S for mod-cure), to claim (with probability pr\_def3\_clm\_S), or to prepay (with probability pr\_def3\_pre\_S). For loans transitioning back to status, the loan categories to be incremented are current0\_S or current0\_M, for self-cure or mod-cure, respectively.

To summarize, the final outputs of the survivorship calculations for each period are updated values of the percentage of survivors with current and default statuses delineated by duration of default, or duration of cure, and the path dependence indicators S and M reflecting whether the loan had a prior default and self-cure (S) or a prior default and a modification (M). These include the following:

current0      – current status never defaulted

- current0\_S to current5\_S – current status with prior default and self-cure by duration of cure
- current0\_M to current5\_M – current status with prior default and mod-cure by duration of default
- default0 – default status with no prior self-cure or mod-cure
- default0\_S to default5\_S – default status with prior default and self-cure by duration of default
- default0\_M to default5\_M – default status with prior default and mod-cure by duration of default

We note that the status current0\_M provides an estimate of the share of surviving loans that have recently returned to current status after receiving a loan modification. In this case, the status current0\_M volume reflects the timing and incidence of mod-cures to which an estimate of modification partial claim severity may be applied to estimate the timing and magnitude of these partial claim expenses.

For example, we know loans in this status are recently cured because the duration of cure is 0, corresponding to the first quarter in a cured state. We know the loan was previously modified as denoted by the M component of the status code. And we assume that the majority of loans receiving a loan modification only receive a single modification over the entire life of the loan so that the timing of the mod cure coincides with entry to this status. Finally, we know that any loan spends only one quarter in this status since in the next quarter duration increases and they are promoted to status current1\_M, so current0\_M is specific to the quarter in which it is reported.

The outputs of the survivorship programs retain the additional detail on original loan characteristics such as case\_nbr, product, LTV, credit score, original loan amount, DPA type, and geographic location that may be needed for linking to other SFDW information related to the cash flow analysis (upfront- and annual-premia, partial claim loss amounts, full claim loss amounts, etc.).

## Appendix D. Loss Severity and Cash Flow Analysis

### D1. Introduction

The calculation of the economic net worth of the Fund involves the estimation of the present value of future cash flows generated by the existing portfolio into the future. The analysis requires the projection of future prepayment and claims incidents, and severity and cash flow items associated with each type of outcome. This Appendix describes the components of these cash flow calculations.

The evaluation of the Fund's economic net worth at a point in time (e.g. FY 2025) requires the addition of the value of net assets and the expected present value of future cash flows. The latter comprises future revenue and expenses. The actuarial model uses projections from econometric models as discussed in Appendices A-E.

We estimated econometric models for conditional transition probabilities for individual loans depending on the loan type, origination year, age, interest rate, loan purpose, initial and current LTV ratio, credit score, refinancing incentive, relative loan size, loan term, interest rate and credit burnouts, and other characteristics. The models also used data on serious delinquency status and default history. Using detailed loan-level characteristics, we estimated the various transition probabilities (Appendix A) and then generated respective cash flows for individual loans.

We estimated an econometric model of loss severity rates (Appendix D). The loss rate model distinguishes between pre-foreclosure sales, conveyance, and third-party sales. We estimated future FHA mortgage volumes for purchase, refinance, and streamlining refinance mortgages that vary with alternative house prices, unemployment rates, and interest rate paths. Based on the mortgage termination rates projected by the econometric models, individual components of cash flows are projected into the future. These cash flows are discounted to the present time based on the MMI Single Effective Rate discount factors provided by FHA. The relevant cash flow components are itemized in Exhibit D-1.

Exhibit D-1. Cash Flow Components

| Cash Flow Component     | Inflow | Outflow |
|-------------------------|--------|---------|
| Upfront Premiums        | X      |         |
| Annual Premiums         | X      |         |
| Upfront Premium Refund  |        | X       |
| Loss Mitigation Expense |        | X       |
| Claim Expenses          |        | X       |
| Recoveries              | X      |         |

These components were projected quarterly for individual loans and then aggregated according to the product type and cohort year for reporting purposes. Below, we discuss the derivation of each of these cash flows,

The following definitions and background information clarify our discussion of the cash flow components:

**Insurance-in-Force (IIF):** the nominal value of the unamortized original mortgage loan balances of the surviving mortgages insured by FHA. This is distinct from the conventional notion of amortized insurance-in-force, which includes only the current outstanding balances on surviving loans.

**Conditional Claim Rate (CCR):** the number of loans that become claims during a time divided by the number of surviving loans in force at the beginning of that period.

**Conditional Prepayment Rate (CPR):** the number of loans being completely prepaid during a time divided by the number of surviving loans-in-force at the beginning of that period.

**Policy Year:** measures the number of fiscal years since origination. The year in which the mortgage originated is assigned as fiscal policy year one.

**Termination Year:** the fiscal year in which a mortgage terminates through a claim, prepayment, or other reasons.

**Unpaid Principal Balance (UPB) Factor:** the principal balance outstanding at a given time divided by the original mortgage amount. The UPB factor is calculated based only on amortization, given the original maturity, the type of mortgage, and the mortgage contract rate. For FRMs, the UPB factor for each quarter in the future can be directly computed using the initial contract rate and the amortization term. For ARMs, the UPB factor changes depending on the interest rate of the loan, which is updated according to the contractual rate adjustment rule. In our model, the contract interest rates of ARM loans are updated by using changes in the 1-year Treasury rate as an approximation for changes in the underlying index, subject to limits implied by FHA annual and lifetime rate adjustment caps.

## D2. Cash Flow Components

### D2.1. Premiums

#### D2.1.1. Premium Structure

The primary source of revenue for the Fund is insurance premiums. If the Fund's mortgage insurance is priced to meet the expected liabilities, the insurance premiums collected and interest earned on them will cover all costs associated with mortgage loans insured by the Fund, under a normal economic environment. The insurance premium has been structured in different ways during different periods.



For loans originated before September 1, 1983, the mortgage premium was collected monthly at an annualized rate of 0.50 percent of the outstanding principal balance for the period. To align this change with fiscal quarters, we assumed that this annual premium policy was in effect through September 30, 1983.

Between September 1, 1983, and June 30, 1991, the mortgage premium was charged only upon loan origination and was based on a percentage of the original mortgage amount at the time of origination. This amount was 3.80 percent for 30-year mortgages and 2.40 percent for 15-year mortgages.

Effective July 1, 1991, the National Affordable Housing Act specified a new premium structure. This structure specified an upfront premium of 3.80 percent for all product types except for 15-year non-streamline refinance loans (for which the upfront premium was set at 2.00 percent) and an annual renewal premium of 0.50 percent per year on the outstanding balance. The annual premium would cease at different policy years depending on the initial LTV of the loan.

- On October 1, 1992, the upfront premium for 30-year mortgages was reduced from 3.80 percent to 3.00 percent. The annual premium for 30-year mortgages was extended for a longer time, while for 15-year mortgages it was lowered to 0.25 percent for a shorter time or completely waived if the initial LTV ratio was less than 90 percent.
- As of April 17, 1994, FHA lowered the upfront premium rate on 30-year mortgages from 3.00 percent to 2.25 percent. To align this change with fiscal quarters, we started applying this policy change on April 1, 1994.
- Starting from October 1, 1996, FHA lowered the upfront premium rate on 30-year mortgages for first-time homebuyers who receive homeowner counseling from 2.25 percent to 2.00 percent. This rate was further reduced to 1.75 percent for mortgages executed on or after September 22, 1997. This favorable treatment for borrowers with homeownership counseling was terminated shortly thereafter.
- Effective January 1, 2001, FHA lowered the upfront premium rate for all mortgages to 1.50 percent. The annual premium would stop as soon as the current LTV ratio of the loan was below 78 percent according to the home price as of the loan origination date. The annual premium was required to be paid for a minimum of five years for 30-year mortgages.
- Effective October 1, 2008, FHA charged an upfront premium rate of 1.75 percent for purchase money mortgages and full-credit qualifying refinances; and 1.50 percent for all types of streamline refinance loans. A varying annual premium, remitted monthly, was charged based on the initial loan-to-value ratio and maturity of the mortgage.
- Effective April 1, 2010, FHA changed the upfront premium to 2.25 percent for all mortgages executed after April 1, 2010.

- Effective October 4, 2010, FHA lowered the upfront premium of all mortgages to 1.0 percent. The annual premium for loans with 30-year terms was increased to 0.85 percent for LTV ratios up to 95 percent and 0.90 percent for LTV ratios greater than 95 percent. For loans with 15-year terms, an annual premium of 0.25 percent was set for LTV ratios greater than 90 percent. To align this change with fiscal quarters, we started applying this policy change on October 1, 2010.
- Effective April 18, 2011, the annual premium for loans with 30-year terms was increased to 1.10 percent for LTV ratios up to 95 percent and 1.15 percent for LTV ratios greater than 95 percent. For loans with 15-year terms, the annual premiums were increased to 0.25 percent for LTV ratios up to 90 percent and to 0.50 percent for LTV ratios greater than 90 percent. To align this change with fiscal quarters, we started applying this policy change on April 1, 2011.
- Effective April 9, 2012, FHA increased the upfront premium of all mortgages to 1.75 percent. The annual premium for loans with 30-year terms was increased to 1.20 percent for LTV ratios up to 95 percent, and 1.25 percent for LTV ratios greater than 95 percent. For loans with 15-year terms, the annual premiums were increased to 0.35 percent for LTV ratios up to 90 percent, and 0.60 percent for LTV ratios greater than 90 percent. To align this change with fiscal quarters, we started applying this policy change on April 1, 2012.
- Effective June 11, 2012, the annual premium for loans with 30-year terms and base loan amounts above \$625,500 was increased to 1.45 percent for LTV ratios up to 95 percent, and 1.50 percent for LTV ratios greater than 95 percent. For loans with 15-year terms, and a base loan amount above \$625,500, the annual premium was increased to 0.60 percent for LTV ratios up to 90 percent, and to 0.85 percent for LTV ratios greater than 90 percent. Also, effective June 11, 2012, for all single-family forward streamline refinance loans which are refinancing existing FHA loans that were endorsed on or before May 31, 2009, the upfront premium decreased to 0.01 percent of the base loan amount, and the annual premium was set at 0.55 percent, regardless of the base loan amount. To align this change with fiscal quarters, we started applying this policy change on July 1, 2012.
- Effective April 1, 2013, the annual premium for loans with 30-year terms and base loan amounts below \$625,500 was increased to 1.30 percent for LTV ratios up to 95 percent, and 1.35 percent for LTV ratios greater than 95 percent. The annual premium for loans with 30-year terms and base loan amounts above \$625,500 was increased to 1.50 percent for LTV ratios up to 95 percent, and 1.55 percent for LTV ratios greater than 95 percent. For loans with 15-year terms and base loan amounts below \$625,500, the annual premium was increased to 0.45 percent for LTV ratios up to 90 percent, and 0.70 percent for LTV ratios greater than 90 percent. For loans with 15-year terms and base loan amounts above \$625,500, the annual premium was increased to 0.70 percent for LTV ratios up to 90 percent, and to 0.95 percent for LTV ratios greater than 90 percent. This increase was

effective for all forward mortgages except single-family forward streamline refinance transactions that refinance existing FHA loans that were endorsed on or before May 31, 2009.

- Effective June 3, 2013, the annual premium rates for loans with an LTV of less than or equal to 78 percent and with terms of up to 15 years was 0.45 percent. The new payment period for annual premiums for loans with case numbers assigned on or after June 3, 2013, and with an LTV up to 90 percent was 11 years, and the annual premium applied for the life of the loan for LTVs greater than 90 percent. To align this change with fiscal quarters, we started applying these policy changes on July 1, 2013.
- Effective January 26, 2015, the annual premium rates for loans with a term greater than 15 years have been reduced by 50 basis points. To align this change with fiscal quarters, we started applying these policy changes effective January 1, 2015.
- Effective March 20, 2023, Mortgagee Letter 2023-05, an annual premium rate reduction of 30 basis points was issued for all mortgages except streamline refinance and simple refinance mortgages on previous FHA endorsed mortgages on or before May 31, 2009 along with Hawaiian Home Lands (HHL).
- Effective January 1, 2024, the threshold for one-unit loans in high-cost areas was increased from \$1,089,300 to \$1,149,825 pursuant to Mortgage Letter 2023-01.

#### D2.1.2. Upfront Premium

The upfront premium is assumed to be fully paid at the mortgage origination date, and the amount is calculated as follows:

$$\text{Upfront Premium Payment} = \text{Origination Loan Amount} * \text{Upfront Insurance Premium Rate}$$

In practice, FHA allows a premium finance program to those qualified for mortgage insurance, so that the upfront premium does not add to the borrower's equity burden at the beginning of the contract. Instead, the borrower can add it to the original loan balance, in essence paying the upfront premium at the same schedule as their principal balance. The annual premium is charged based on the unpaid principal balance excluding the financed upfront premium. Almost all borrowers finance their upfront premiums in this fashion. However, the LTV including refinanced upfront premiums cannot exceed 96.5 percent.

#### D2.1.3. Annual Premium

The annual premium is calculated as follows:

$$\text{Quarterly Payment of Annual Premium} = \text{UPB (excluding any upfront premiums)} * \text{Annual Insurance Premium Rate} / 4$$

The premium is collected monthly. The above formula models the premium as being collected at the beginning of each quarter for purposes of our analysis. In addition, the termination rate will have an impact on future premium flows. All potential future premium income would no longer be paid when a particular mortgage loan is prepaid or claimed. The annual premium is not assessed on the amount of the financed upfront premium.

## D2.2. Losses Associated with Claims

The Fund's largest expense component comes in the form of payments arising from claims. FHA pays the claim to the lender after a lender files a claim. Traditionally, in most cases, FHA takes possession of the foreclosed property and sells the property to partially recover the loss. This type of claim is called a conveyance.

Based on this practice, claim cash flows can be decomposed into two components:

- Cash outflow of the claim payment at the claim date including expenses incurred, and
- Cash inflow of any net proceeds received in selling the conveyed property at the property disposition date.

For tractability, we simplify this two-step cash flow into one lump sum amount. We also separately estimate losses from pre-foreclosure sales, wherein the property is sold before the completion of a foreclosure, and the property is not conveyed to HUD, and losses from third-party sale. The claim loss payment estimated in our model at time  $t$  is

$$ClaimLoss_t = UPB_t * LossRate_t$$

For this review, we applied a dynamic simulation approach that tracks loan transitions to default, claim, and prepayment that reflect the probabilities of the various transitions (see Appendix A). The  $UPB_t$  is the amount of the unpaid balance of the loan at the beginning of time  $t$  for loans that terminate at time  $t$  with a claim.

The loss rate is usually referred to as the loss-given default (LGD) or “severity” in the banking industry. It measures the amount of principal not recovered from property sale and expenses incurred in property acquisition, holding, and sales. This amount is divided by the unpaid principal balance at the time of claim. The portfolio-level loss rate is predicted as the weighted average loss rates among conveyance, pre-foreclosure sales, and the implemented policy of third-party sales, where the weights reflect the probability that a claim is associated with the individual types of claims. Note that since the beginning of FY 2018, there have been no Single Family Forward note sales per the data provided by FHA and per the disclosure of note sales provided publicly by FHA's Office of Asset Sales. This disposition type currently is excluded from disposition modeling due to minimal historical activity since FY 2018. However, this disposition type may be modeled in future studies based on potential future policy changes that trigger new Single Family Forward note sales. The loss rate formulation is as follows:

$$\begin{aligned} \text{LossRate}_t = & (\text{Probability of PFS} \times \text{LossRate}_{\text{PFS}}) \\ & + (\text{Probability of REO} \times \text{LossRate}_{\text{REO}}) \\ & + (\text{Probability of TPS} \times \text{LossRate}_{\text{TPS}}) \end{aligned}$$

To model the probabilities of Pre-Foreclosure Sale (PFS), Third Party Sale (TPS), and Real Estate Owned (REO) dispositions, a multinomial logistic regression model was deployed to estimate the likelihood that a property would undergo a PFS transaction or a TPS transaction for loan claim  $k$  using explanatory variables  $\mathbf{X}$  defined in Appendix A.

$$\begin{aligned} P(\text{PFS}) &= \frac{e^{\beta_{\text{PFS}}\mathbf{X}_k}}{1 + e^{\beta_{\text{PFS}}\mathbf{X}_k} + e^{\beta_{\text{TPS}}\mathbf{X}_k}} \\ P(\text{TPS}) &= \frac{e^{\beta_{\text{TPS}}\mathbf{X}_k}}{1 + e^{\beta_{\text{PFS}}\mathbf{X}_k} + e^{\beta_{\text{TPS}}\mathbf{X}_k}} \end{aligned}$$

The probability of conveyance was calculated by taking the difference of 1 minus the probability of a pre-foreclosure sale less the probability of third-party sales.

$$P(\text{REO}) = 1 - P(\text{PFS}) - P(\text{TPS})$$

Following the estimation of the disposition probabilities, we calculate the loss rates of each of the dispositions. Generalized least-squares regression was deployed to estimate the PFS, TPS, and REO loss rate dispositions respectively, with the explanatory variables described in Appendix A and historical loss rate data from the SFDW as the independent variable.

The historical loan disposition shares (excluding note sales) from fiscal year 1995 to 2025 are displayed in Exhibit D-2. As illustrated in Exhibit D-2, REO made up most of the HUD's recovery on claimed assets from experience years 1994 through 2012. However, since 2012, TPS have quickly overtaken REO as the most utilized disposition method. Examining this historical trend in loss severity disposition, we determined that data including experience years from 2009 to 2025 is more in line with the current state of claim recoveries.

It is also important to note that the historical claim counts are significantly less in recent years than the period before 2015, as displayed in Exhibit D-3. As a result, the REO disposition remains dominant in the estimation sample in terms of counts, which can distort the forecasting power of the model. To better reflect the recent trends of claim disposition in forecasting, we adopted a weighting approach so that each experience period has the same importance level in model estimation. Specifically, instead of imposing equal weights on each observation, we assign the same total weights to each experience quarter and then equally allocate the weights to each observation within the quarter.



Exhibit D-2: Loss Severity Share by Disposition Type

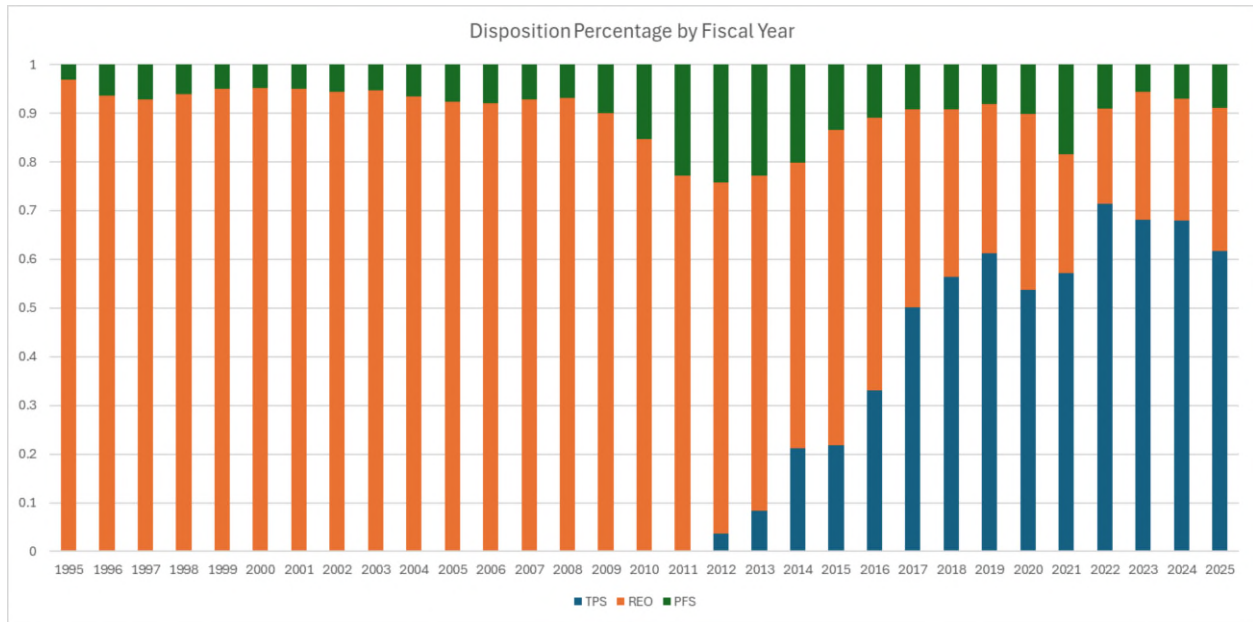
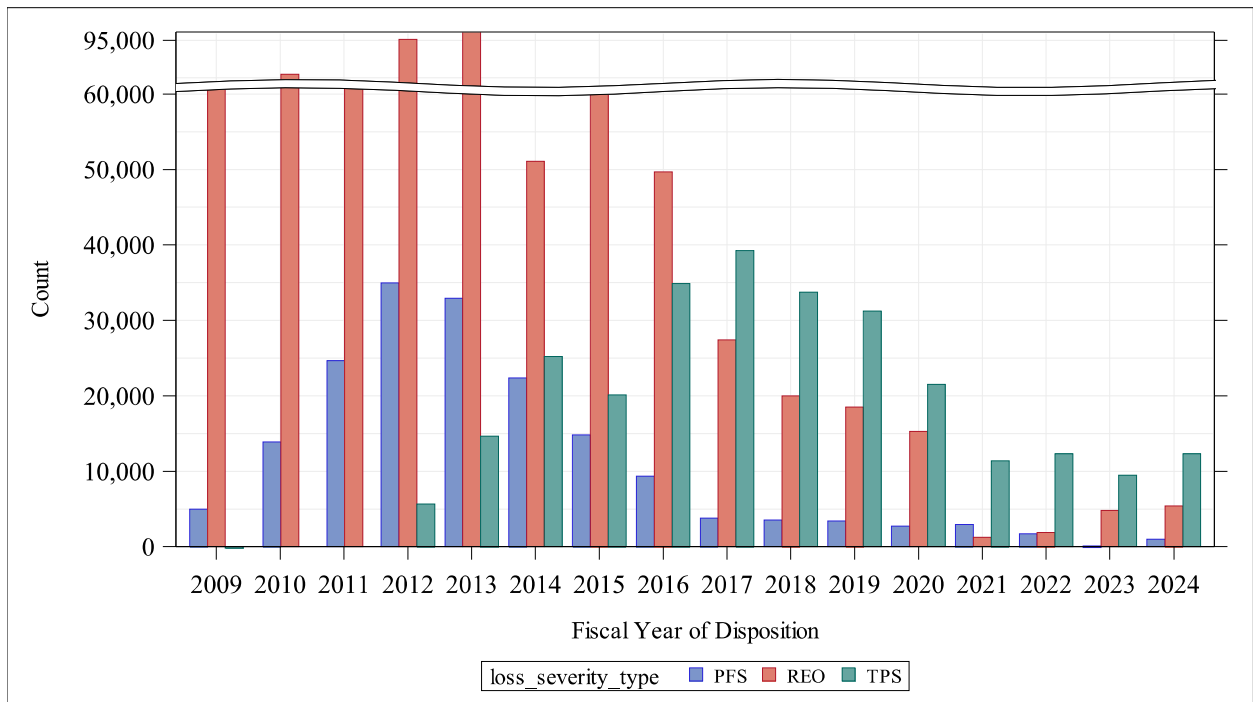


Exhibit D-3: Loss Severity Counts by Disposition Type



The estimation of the loss severity rate models utilized loan-level data from the FHA single-family data warehouse for conveyance, pre-foreclosure, and third-party sale claims from experience years 1995 to 2025. Prior to 2012, there were no TPS claims. Due to COVID loss mitigation policy, we also find that the loss counts since 2019 for all three claim types were much smaller than those in previous experience years. The historical loss severity rates for REO disposition before and after 2012 can be different due to the fact that loans disposed through REO after 2012 tend to be those loans that could not or would not be disposed through TPS or note sale. Nevertheless, including data before 2012 can help the GLM model learn the loan differences before and after 2012 and better capture the determinants of REO severity as well as its trend. Therefore, it is appropriate to incorporate as much data as possible for REO severity estimation. Our validation results reported in Exhibit D-13 provide strong evidence that the estimated model based on the selected data period effectively identified the distinctions between REO loss severity levels before and after 2012.

The final sample used for estimation included 56,471 loans claimed over the timeframe.<sup>78</sup> Both the loss severity disposition model and loss severity rate models went through comprehensive collinearity tests and variable selection process through the Lasso procedure. The following tables include the estimated parameters for the models, including the coefficients, Chi-square, and t-statistics confirming the sufficiency of the model specification.

Exhibit D-4: Loss Severity Disposition Model Parameters

| Description                                            | Parameter        | Loss Severity Type | Estimate | Wald Chi-Square | Pr > ChiSq |
|--------------------------------------------------------|------------------|--------------------|----------|-----------------|------------|
|                                                        | Intercept        | PFS                | 1.0511   | 3.7397          | 0.0531     |
|                                                        | Intercept        | TPS                | -9.0147  | 513.0529        | <.0001     |
| Log Loan Age                                           | Agelog           | PFS                | -0.9943  | 654.1104        | <.0001     |
|                                                        | Agelog           | TPS                | 1.2258   | 1328.3673       | <.0001     |
| ARM Payment Shock                                      | arm_pmt_shock    | PFS                | 0.0125   | 82.4573         | <.0001     |
|                                                        | arm_pmt_shock    | TPS                | 0.0038   | 10.8308         | 0.0010     |
| Loan Beginning Amortization Date                       | beg_amort_dt     | PFS                | -0.0002  | 88.2868         | <.0001     |
|                                                        | beg_amort_dt     | TPS                | 0.0004   | 924.8495        | <.0001     |
| Loan-level Mortgage Interest Rate                      | Coupon           | PFS                | -0.1674  | 69.2867         | <.0001     |
|                                                        | Coupon           | TPS                | -0.0842  | 26.1531         | <.0001     |
| Current Number of Consecutive Quarters Loan Underwater | credit_burnout   | PFS                | 0.0087   | 26.3504         | <.0001     |
|                                                        | credit_burnout   | TPS                | -0.0036  | 10.5021         | 0.0012     |
| Credit Score                                           | credit_score_FHA | PFS                | 0.2243   | 43.3192         | <.0001     |

<sup>78</sup> There are a tiny portion of loans terminated through CWCOT outbids, in which case the sales proceeds from the CWCOT auction are large enough such that filing a claim is not necessary. These incidents are excluded from claim counts in our estimation.

| Description                                            | Parameter               | Loss Severity Type | Estimate                     | Wald Chi-Square | Pr > ChiSq |
|--------------------------------------------------------|-------------------------|--------------------|------------------------------|-----------------|------------|
|                                                        | credit_score_FHA        | TPS                | 0.1029                       | 13.3585         | 0.0003     |
| Deficiency Judgement State                             | Deficiency              | PFS                | 0.0590                       | 2.5021          | 0.1137     |
| Indicator                                              | Deficiency              | TPS                | 0.1303                       | 15.7820         | <.0001     |
| Front-End DTI                                          | dti_front_end           | PFS                | 0.0034                       | 10.5874         | 0.0011     |
|                                                        | dti_front_end           | TPS                | 0.0053                       | 34.3699         | <.0001     |
| Quarterly Primary Market FRM 30 Mortgage Interest Rate | ey_rate                 | PFS                | -0.1527                      | 32.5080         | <.0001     |
|                                                        | ey_rate                 | TPS                | -0.2297                      | 119.1489        | <.0001     |
| Local Home Price Appreciation Since Origination        | hpa_local               | PFS                | 3.9522                       | 233.2109        | <.0001     |
|                                                        | hpa_local               | TPS                | 7.7448                       | 398.0430        | <.0001     |
| Squared Local Home Price Appreciation                  | hpa_local_sq            | PFS                | -5.0170                      | 45.2562         | <.0001     |
|                                                        | hpa_local_sq            | TPS                | -15.8933                     | 227.8272        | <.0001     |
| National Home Price Appreciation                       | hpa_usa                 | PFS                | 3.1984                       | 114.2862        | <.0001     |
|                                                        | hpa_usa                 | TPS                | 3.6040                       | 220.7625        | <.0001     |
| Indicator, Credit Score >= 620                         | ind_credit_score_ge_620 | PFS                | -0.3982                      | 162.0547        | <.0001     |
|                                                        | ind_credit_score_ge_620 | TPS                | 0.0228                       | 0.7791          | 0.3774     |
| Indicator, Loan Size 100-160% of State Average         | ind_loansize_100_160    | PFS                | -0.0902                      | 9.2074          | 0.0024     |
|                                                        | ind_loansize_100_160    | TPS                | -0.0851                      | 9.0739          | 0.0026     |
| Indicator, Current LTV <= 100                          | ind_ltvcurrent_le_100   | PFS                | -0.0135                      | 0.1165          | 0.7328     |
|                                                        | ind_ltvcurrent_le_100   | TPS                | -0.0813                      | 4.6209          | 0.0316     |
| Indicator, Judicial Foreclosure State                  | Judicial                | PFS                | -0.1903                      | 41.4870         | <.0001     |
|                                                        | Judicial                | TPS                | 0.1267                       | 27.9776         | <.0001     |
| Ratio of Original Loan Amount to State Average         | Loansize                | PFS                | 0.0084                       | 478.5942        | <.0001     |
|                                                        | Loansize                | TPS                | -0.0005                      | 2.0828          | 0.1490     |
| Original Loan Term Recoded to 180 or 360               | Loanterm                | PFS                | 0.0067                       | 136.3322        | <.0001     |
|                                                        | Loanterm                | TPS                | -0.0002                      | 0.3996          | 0.5273     |
| Change in Unemployment Rate, t-3 to t-1                | ue_delta                | PFS                | -0.0719                      | 61.4879         | <.0001     |
|                                                        | ue_delta                | TPS                | 0.0292                       | 13.6207         | 0.0002     |
| Squared Change in Unemployment Rate                    | ue_relative_sqrt        | PFS                | 1.8705                       | 176.6399        | <.0001     |
|                                                        | ue_relative_sqrt        | TPS                | -2.1226                      | 347.6134        | <.0001     |
| Model Fit Statistics                                   |                         |                    |                              |                 |            |
| Chi-Square Statistic                                   |                         |                    | 24378.05 (df=40, p < 0.0001) |                 |            |
| Adjusted R-Square                                      |                         |                    | 0.5914                       |                 |            |

Exhibit D-5: Loss Rate Given Conveyance (REO) Model Parameters

| Description | Parameter | Estimate | t Value | Pr >  t |
|-------------|-----------|----------|---------|---------|
|-------------|-----------|----------|---------|---------|

|                                                        |                         |         |        |        |
|--------------------------------------------------------|-------------------------|---------|--------|--------|
| Intercept                                              | Intercept               | 0.4249  | 6.94   | <.0001 |
| ARM Payment Shock                                      | arm_pmt_shock           | -0.0015 | -12.78 | <.0001 |
| Indicator, Condominium                                 | condo_prop              | -0.0846 | -3.96  | <.0001 |
| Loan-level Mortgage Interest Rate                      | Coupon                  | 0.0132  | 8.81   | <.0001 |
| Indicator, COVID Loss Mitigation Period                | covid_lossmit           | -0.1394 | -6.3   | <.0001 |
| Indicator, Missing Credit Score                        | credit_score_MISSING    | -0.0371 | -10.2  | <.0001 |
| Deficiency Judgement State Indicator                   | Deficiency              | 0.0775  | 20.44  | <.0001 |
| Quarterly Primary Market FRM 30 Mortgage Interest Rate | ey_rate                 | -0.0524 | -33.33 | <.0001 |
| FICO Score Category                                    | fico_cat                | -0.0064 | -7.09  | <.0001 |
| Local Home Price Appreciation Since Origination        | hpa_local               | -0.9855 | -70.27 | <.0001 |
| Indicator, Judicial Foreclosure State                  | Judicial                | 0.0910  | 29.32  | <.0001 |
| Living Units Equals 2                                  | liv_units_2             | 0.1812  | 14.44  | <.0001 |
| Original Loan Term Recoded to 180 or 360               | Loanterm                | -0.0002 | -2.94  | 0.0033 |
| Change in Unemployment Rate, t-3 to t-1                | ue_delta                | -0.0124 | -6.53  | <.0001 |
| Indicator, Current LTV <= 80                           | ind_ltvcurrent_le_80    | -0.0671 | -18.1  | <.0001 |
| Indicator, Current LTV <= 90                           | ind_ltvcurrent_le_90    | -0.0691 | -18.89 | <.0001 |
| Indicator, Current LTV > 150                           | ind_ltvcurrent_gt150    | -0.0408 | -6.29  | <.0001 |
| Indicator, Loan Size 100-160% of State Average         | ind_loansize_100_160    | -0.0295 | -8.17  | <.0001 |
| Cube-root of Loan Size                                 | Loansizecubrt           | -0.1454 | -39.09 | <.0001 |
| Indicator, Loan Age <= 20                              | ind_loanage_le_20       | -0.1236 | -37.68 | <.0001 |
| Cube-Root of HPI Market Volume                         | hpi_mkt_vol_cubrt       | 3.0358  | 24.29  | <.0001 |
| Indicator, Credit Score >= 620                         | ind_credit_score_ge_620 | -0.0169 | -4.1   | <.0001 |
| Model Fit Statistics                                   |                         |         |        |        |
| R-Square                                               |                         | 0.4001  |        |        |

Exhibit D-6: Loss Rate Given PFS Model Parameters

| Description                       | Parameter | Estimate | t Value | Pr >  t |
|-----------------------------------|-----------|----------|---------|---------|
| Intercept                         | Intercept | -0.6135  | -6.89   | <.0001  |
| Loan-level Mortgage Interest Rate | Coupon    | -0.0076  | -5.32   | <.0001  |

|                                         |                         |          |        |        |
|-----------------------------------------|-------------------------|----------|--------|--------|
| Deficiency Judgement State Indicator    | Deficiency              | 0.0668   | 11.52  | <.0001 |
| Indicator, Front-End DTI Missing        | dti front_end MISSING   | 0.0419   | 8.63   | <.0001 |
| Indicator, Judicial Foreclosure State   | Judicial                | 0.0138   | 2.74   | 0.0062 |
| Living Units Equals 2                   | liv_units_2             | 0.1719   | 8.68   | <.0001 |
| Change in Unemployment Rate, t-3 to t-1 | ue_delta                | -0.0126  | -4.84  | <.0001 |
| Indicator, Current LTV <= 80            | ind_ltvcurrent_le_80    | -0.0519  | -7.34  | <.0001 |
| Indicator, Current LTV <= 90            | ind_ltvcurrent_le_90    | -0.0838  | -14.48 | <.0001 |
| Cube-Root of Loan Size                  | Loansizecubrt           | -0.0606  | -13    | <.0001 |
| Log Loan Age                            | Agelog                  | 0.1060   | 26.74  | <.0001 |
| Cube-Root of HPI Market Volume          | hpi_mkt_vol_cubrt       | 2.4901   | 11.96  | <.0001 |
| Indicator, Credit Score >= 620          | ind_credit_score_ge_620 | 0.0107   | 2.2    | 0.0278 |
| Model Fit Statistics                    |                         |          |        |        |
| R-Square                                |                         | 0.214786 |        |        |

Exhibit D-7: Loss Rate Given TPS Model Parameters

| Description                                     | Parameter               | Estimate | t Value | Pr >  t |
|-------------------------------------------------|-------------------------|----------|---------|---------|
| Intercept                                       | Intercept               | -0.4934  | -3.58   | 0.0004  |
| Indicator, COVID Loss Mitigation Period         | covid_lossmit           | -0.1267  | -9.25   | <.0001  |
| Local Home Price Appreciation Since Origination | hpa_local               | -0.7500  | -12.25  | <.0001  |
| Indicator, Judicial Foreclosure State           | Judicial                | 0.1591   | 20.68   | <.0001  |
| Living Units Equals 2                           | liv_units_2             | 0.1905   | 5.85    | <.0001  |
| Indicator, Current LTV <= 80                    | ind_ltvcurrent_le_80    | -0.0611  | -7.68   | <.0001  |
| Cube-Root of Loan Size                          | Loansizecubrt           | -0.1155  | -17.38  | <.0001  |
| Cube-Root of HPI Market Volume                  | hpi_mkt_vol_cubrt       | 3.4090   | 10.6    | <.0001  |
| Indicator, Credit Score >= 620                  | ind_credit_score_ge_620 | -0.0922  | -12.16  | <.0001  |
| Squared Change in Unemployment Rate             | ue_relative_sqrt        | 0.2483   | 7.81    | <.0001  |
| Model Fit Statistics                            |                         |          |         |         |
| R-Square                                        |                         | 0.209454 |         |         |

The multivariate logistic regression model predicting loss disposition types demonstrated good data fitting with an adjusted R-Square of 0.5914. The GLM model for REO loss rates also provides satisfactory explanation power with an R-Square of 0.4001. For PFS and TPS loss rates, fewer



significant variables were identified, and the fitted GLM models have R-Square of 0.2148 and 0.2095, respectively. However, this is reasonable, given that the sample sizes of PFS and TPS are significantly smaller than those of REO. Overall, loss recovery rates can be affected by many subjective factors that are difficult to capture by quantitative models. Importantly, all the loss severity rate models provide reasonable predictive power as demonstrated in model validation, which are shown in Section D3.3.

### D2.3. Loss Mitigation Expenses

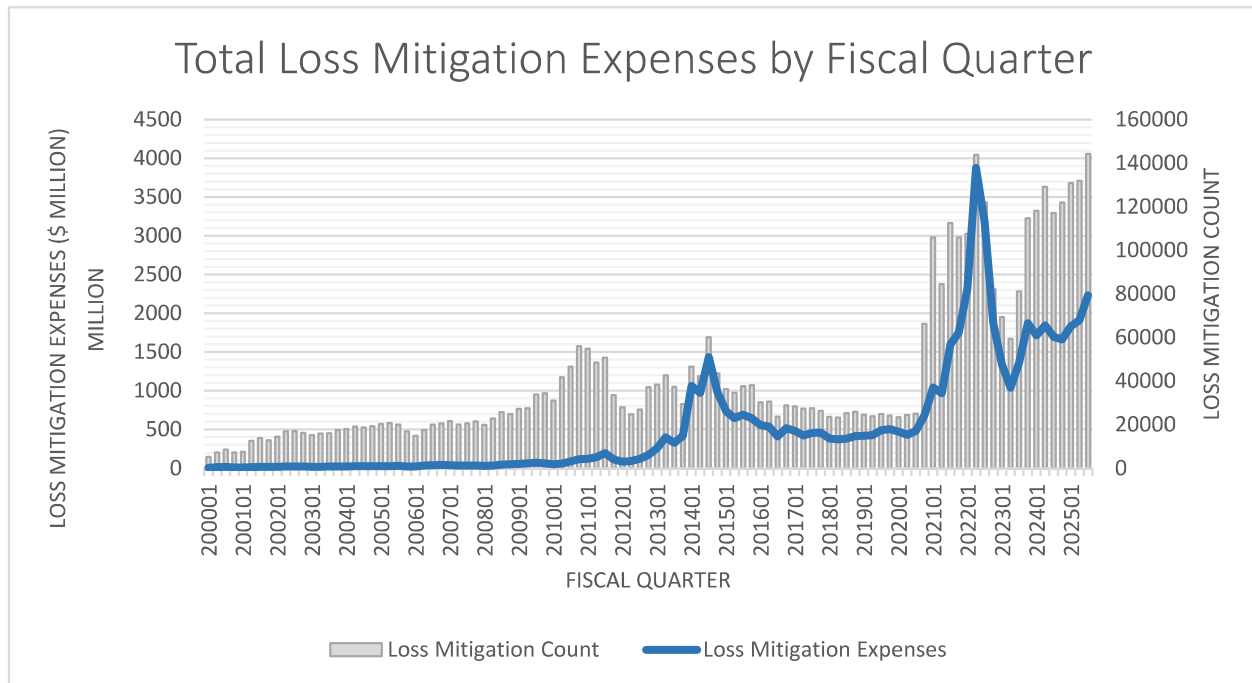
HUD initiated a loss mitigation program in 1996 to provide opportunities for borrowers in financial difficulties to retain homeownership. Loss mitigation also reduces foreclosure costs. In the standard process, mortgages provide default counseling for borrowers who are behind in their payments and offer appropriate loss mitigation options to prevent borrowers from losing their homes. In 2009, FHA started the Home Affordable Modification Program (HAMP) as a new loss mitigation option, and the program represented increasing percentages of loss mitigation assistance through the years. In 2016, Loan Modification as a standalone option was eliminated and combined into HAMP.

The loss mitigation program includes Forbearance and HAMP, which has Loan Modification and Partial Claim options. A Special Forbearance is a written repayment agreement between the mortgagee, acting on behalf of FHA, and the borrower that contains a plan to reinstate a loan.

Loan Modification modifies the contractual terms of the mortgage permanently, such as lowering the interest rate, or increasing the loan term. Under the partial claim option, a mortgagee will advance funds on behalf of a mortgagor in an amount necessary to reinstate a delinquent loan. The borrowers are required to sign a promissory note and a subordinated mortgage payable to FHA for the amount advanced. Loss mitigation payments made by FHA may include administrative fees and costs of title searches, recording fees, subordinated mortgage note amounts associated with partial claims and the payment supplement program, and costs associated with preforeclosure sales.

Exhibit D-8 shows the historical loss mitigation expenses by fiscal quarter, setting aside preforeclosure sales and third-party sales, which are captured separately under the loss severity model discussion.

Exhibit D-8: Loss Mitigation Expenses<sup>79</sup>



The expected value of loss mitigation is as follows:

$$\text{Loss Mitigation Expected Value} = (P(\text{Loss Mitigation}) \times (\text{Loss Mitigation Expense}))$$

This model estimates total costs associated with loss mitigation. These costs are incorporated into future FHA cashflows that are discounted as part of the net present value (NPV) calculation.

The model uses a comprehensive dataset drawn from FHA's single-family data warehouse. This dataset includes a wide range of loans that have undergone various forms of loss mitigation, offering a strong empirical base for analysis.

We use a Generalized Linear Model (GLM) for loss mitigation rate estimation with LASSO variable selection, tailored to the specific characteristics of the data—namely, that the target variable (loss mitigation expense as a percentage of UPB) will be continuous, strictly positive, and right-skewed. The model uses a gamma distribution for the response variable for modeling cost data where the variance increases with the mean. A log link function is used to relate the linear predictor (a weighted sum of the independent variables) to the expected value of the loss mitigation expense rate. This ensures that the model's predictions remain positive and are interpretable in multiplicative terms.

The estimation of loss mitigation expenses utilized loan-level data of historical mitigations from the FHA single-family data warehouse from 1997 to 2025. The sample used for estimation

<sup>79</sup> Source: SFDQ IDB\_1;

included 52,602 loans with associated loss mitigation over the timeframe. The following table includes the model parameters for the loss mitigation expense estimates, including the coefficients, standard error, and Chi-square statistics.

Exhibit D-9: Loss Mitigation Expense Model Parameters

| Description                                                                          | Parameter             | Estimate | Standard Error | Wald Chi-Square | Pr > ChiSq |
|--------------------------------------------------------------------------------------|-----------------------|----------|----------------|-----------------|------------|
| Intercept                                                                            | Intercept             | -2.182   | 0.1077         | 410.46          | <.0001     |
| Loan-level Mortgage Interest Rate                                                    | Coupon                | -0.1315  | 0.0105         | 157.04          | <.0001     |
| Indicator, COVID Loss Mitigation Period                                              | covid_lossmit         | 0.8549   | 0.0374         | 523             | <.0001     |
| Front-End DTI                                                                        | dti_front_end         | 0.0067   | 0.0011         | 38.69           | <.0001     |
| Indicator, Front-End DTI Missing                                                     | dti_front_end_MISSING | 0.1745   | 0.0346         | 25.42           | <.0001     |
| Refinance Burnout Measure on Moving Average of Amount Prepayment Option in the Money | in_money              | 0.001    | 0.0001         | 128.92          | <.0001     |
| Indicator, Judicial Foreclosure State                                                | Judicial              | 0.0788   | 0.0157         | 25.34           | <.0001     |
| Original Property Value                                                              | orig_value            | 0.0000   | 0.0000         | 126.63          | <.0001     |
| Relative Difference Between Coupon Rate and Market Refinance Rate                    | Relspread             | 0.0021   | 0.0006         | 12.98           | 0.0003     |
| Change in Unemployment Rate, t-3 to t-1                                              | ue_delta              | 0.0198   | 0.0059         | 11.39           | 0.0007     |
| Yield Curve Slope Ratio (Treasure 10 Year Rate to Treasure 1 Year Rate)              | Ycslope               | 0.0255   | 0.0015         | 284.43          | <.0001     |
| Indicator, Fiscal Period 2012 through 2021 Q2                                        | fy_2012_2021Q2        | 0.5008   | 0.0353         | 200.96          | <.0001     |
| Relative Unemployment Rate                                                           | ue_relative           | -0.5494  | 0.0342         | 257.72          | <.0001     |
| Cube-Root of Loan Size                                                               | Loansizecubrt         | -0.1606  | 0.018          | 79.61           | <.0001     |

As previously discussed, all COVID-19 Recovery Loss Mitigation Options are extended through and will expire on September 30, 2025, and the new “loss mitigation waterfall” will be effective October 1, 2025. While it is challenging to accurately predict the new expense levels without any data under the new loss mitigation waterfall, the loss mitigation expenses under the new waterfall are expected to decrease from the levels during the COVID-19 policy regime, imposing a positive effect on the NPV of the MMI Fund. The new waterfall is overall returning to more restrictive and conservative standards, which are similar to the pre-Covid ones in the following three ways.

First, ML 2025-12 requires mortgagees to obtain certification and documents necessary from borrowers to demonstrate specific financial hardship, similar to the pre-COVID period. In contrast, during the COVID-pandemics no documentation was required to prove the hardship beyond the borrower’s assertion of hardship under the CARES Act, and some streamlined modification options, such as COVID-19 Advance Loan Modification (ALM), were automatically offered to eligible borrowers and did not require borrower contact (ML 2021-15).

Second, ML 2025-12 limits one permanent loss mitigation option every 24 months versus 18 months, representing a return to the same pre-pandemic standard under the FHA-HAMP options (ML 2012-22).

Third, to reduce the increased redefaults under the COVID-19 loss mitigation options, FHA returns to its practice under HAMP of requiring servicers to impose Trial Payment Plans (TPPs) before borrowers could execute any retention options for its permanent waterfall (FHA Annual Report to Congress FY 2024).

While we acknowledge that the new loss mitigation waterfall and the HAMP options before COVID pandemics have differences (e.g., payment supplements and 40-year loan modifications under the new waterfall are not in HAMP), both provide similar structured loss mitigation options, prioritizing forbearance, partial claims, and loan modifications as shown in Exhibit I-1. With the reinforcement of the prudent risk management approach FHA observed prior to COVID pandemics, we cautiously assume that the loss mitigation expense level under the new waterfall can be similar to the levels observed in the data period before the COVID-19 pandemics (i.e., fiscal year 2012 to 2021 Q2). Specifically, to forecast future loss mitigation expense levels, we control the COVID-19 loss mitigation policy effect by setting the COVID loss mitigation indicator as 0 and assign the indicator `fy_2012_2021Q2` as 1 to better align with the policy effects during the pre-pandemics period. Given the uncertainty brought by the new loss mitigation waterfall, sensitivity tests on loss mitigation rates are performed in Section IV – E to assess the magnitude of potential effects.

#### D2.4. Refunded Premiums

FHA first introduced the upfront premium refund program in 1983. It specified that FHA would refund a portion of the upfront premium when a household prepaid its mortgage. The upfront premium was “earned” over the life of the loan. Upon prepayment, an approximation of the unearned upfront premium is returned to the borrower. Therefore, the amount of the refund depends on the time from origination to when the mortgage is prepaid. For modeling purposes, the refund payments are calculated as follows:

$$\text{Refund Payments} = \text{Original UPB} * \text{Upfront Premium Rate} * \text{Refund Rate}$$

For this review, we applied a dynamic simulation approach that tracks loan transitions to default, claim, and prepayment that reflect the probabilities of the various transitions (see Appendix A). Refund payments for each quarter are calculated based on the number of loans repaid in that

quarter. In the past, borrowers always received the upfront premium refund when they prepaid their mortgages before the maturity of the mortgage contract. In 2000, FHA changed its policy so that borrowers would obtain refunds only if they prepaid within the first five years of their mortgage contracts. The most recent policy change at the end of 2004 eliminated refunds for early prepayments of any mortgages endorsed after that date, except for those borrowers who refinanced into a new FHA loan within 3 years following the original endorsement date.

### D3. Economic Net Worth

Once all the above future cash flow components are estimated, their present value can be computed by discounting them at an appropriate rate. The economic net worth is the sum of the present value of future net cash flows plus the current capital resources.

#### D3.1. Discount Factors

The discount factors applied in computing the present value of cash flows are the OMB Single Effective Rates (SER). Our simulations aggregate each future year's cash flows, which are treated as being received at the end of the year. The single effective rates applied for discounting are listed in Exhibit D-10.

Exhibit D-10: OMB Single Effective Rate

| Cohort Year | Single Effective Rate |
|-------------|-----------------------|
| 1996        | 6.80%                 |
| 1997        | 6.59%                 |
| 1998        | 5.93%                 |
| 1999        | 5.93%                 |
| 2000        | 6.20%                 |
| 2001        | 6.12%                 |
| 2002        | 5.48%                 |
| 2003        | 4.76%                 |
| 2004        | 3.71%                 |
| 2005        | 2.33%                 |
| 2006        | 4.55%                 |
| 2007        | 4.61%                 |
| 2008        | 4.88%                 |
| 2009        | 4.47%                 |
| 2010        | 1.67%                 |
| 2011        | 3.72%                 |
| 2012        | 2.04%                 |
| 2013        | 2.41%                 |
| 2014        | 2.98%                 |
| 2015        | 2.30%                 |



| Cohort Year | Single Effective Rate |
|-------------|-----------------------|
| 2016        | 2.43%                 |
| 2017        | 2.65%                 |
| 2018        | 2.81%                 |
| 2019        | 2.68%                 |
| 2020        | 1.40%                 |
| 2021        | 1.42%                 |
| 2022        | 2.36%                 |
| 2023        | 4.07%                 |
| 2024        | 4.58%                 |
| 2025        | 4.71%                 |

### D3.2. Calculating Economic Net Worth

The economic net worth of the Fund as of the end of FY 2025 was calculated first by determining the present value of the future cash flows for all surviving loans as of September 30, 2025. This figure was then added to the capital resources of the Fund, estimated as of the same date.

### D3.3 Cashflow Model Validation and Backtesting

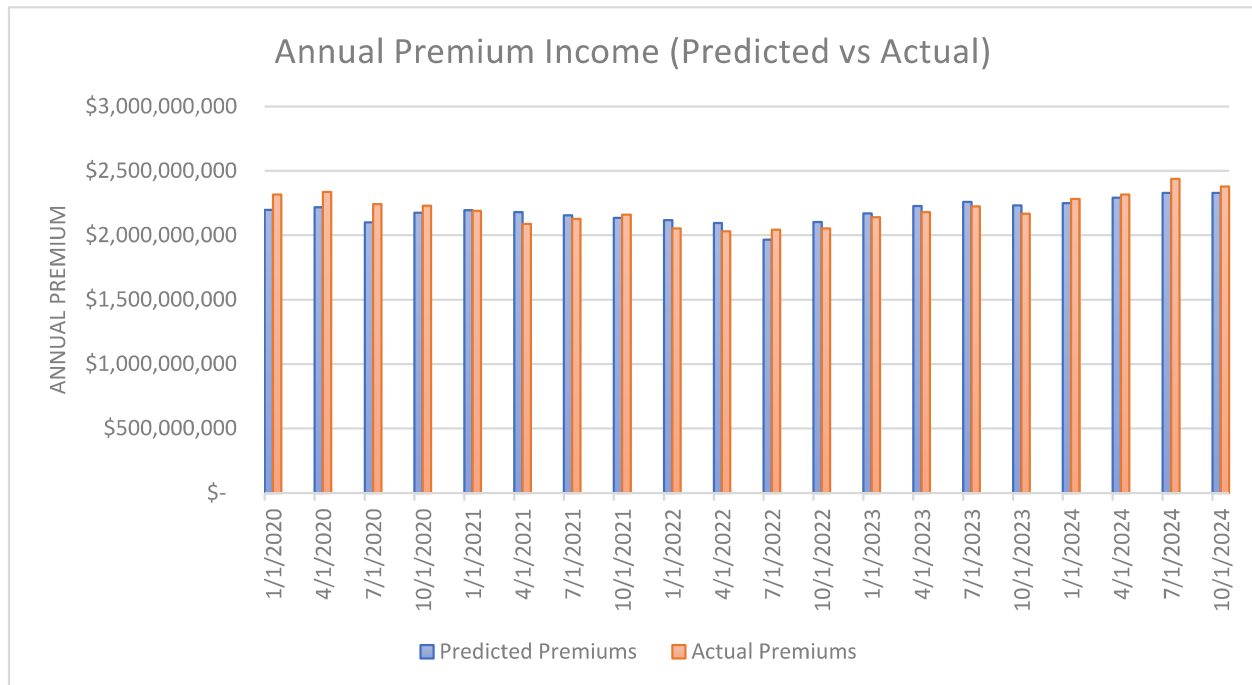
#### D3.3.1 Premium Income

We evaluate premium income forecasting performance by comparing the predicted quarterly premium and refinance repayments with realized outcomes on a rolling basis for a five-year period from FY 2020 Q1 to 2024 Q4. The backtesting data are resampled using the stratified sampling method for each quarter to include a representative sample of all active loans at the beginning of each quarter.

Each quarter we will “walk forward” the loans considered in the survivorship calculation by one quarter, removing conditional termination, to derive projected quarterly premium income and refinance premium outflow for each quarter through 2024 Q4. This is achieved by applying the transition model for each loan, considering dynamically updating loan, borrower, and property characteristics. Premium income projections over the forecast horizon are then derived by applying the appropriate premium formulas to forecasted conditional loan survival data aggregated by origination period, LTV, loan size, and age.

Exhibit D-11 presents the annual premium income backtesting results. Over the five-year period, actual premiums collected totaled \$ 44.0 billion. Predicted premiums were 0.6 percent below actuals at \$43.7 billion. In terms of Mean Absolute Percentage Error, the average difference is at 2.8 percent.

Exhibit D-11: Annual Premium Income Predicted versus Actual



### D3.3.2 Loss Severity

Both the loss selection model and loss severity rate models were tested on the validation data set. The training data set represents 80% of available data, and conversely, the validation data set represents the remaining 20%. Exhibit D-12 presents the predicted loss severity by disposition type. The classification decision thresholds of the logistic regression were determined based on the GHOST (Generalized Threshold Shifting) procedure, which is particularly useful for imbalanced data. The overall accuracy of the prediction was 67.40%, which confirms the effectiveness of the model. The model achieves high sensitivity for REO (71.10%) and TPS (84.84%), indicating most of REO and TPS claims are correctly identified. The recall for PFS is 17.22%, which implies that the model is relatively biased to REO and TPS. This is largely due to the imbalanced proportion of PFS in the sample. On the other hand, the model achieves a precision of 68.46% for PFS, 78.45% for REO, and 49.37% for TPS, indicating that high portion of the model predictions are accurate for each type.

Exhibit D-12: Actual and Predicted Loss Severity by Type

| Loss Severity Type            | Final Prediction Type  |                         |                         |        |
|-------------------------------|------------------------|-------------------------|-------------------------|--------|
| Percent<br>Row Pct<br>Col Pct | PFS                    | REO                     | TPS                     | Total  |
| PFS                           | 2.59<br>17.22<br>68.46 | 8.94<br>59.35<br>16.11  | 3.53<br>23.43<br>8.68   | 15.07  |
| REO                           | 0.63<br>1.02<br>16.54  | 43.55<br>71.10<br>78.45 | 17.08<br>27.88<br>41.96 | 61.25  |
| TPS                           | 0.57<br>2.40<br>15.00  | 3.02<br>12.76<br>5.45   | 20.09<br>84.84<br>49.37 | 23.68  |
| Total                         | 3.79                   | 55.51                   | 40.70                   | 100.00 |

The following three graphs compare the actual and predicted loss severity rates for REO, PFS, and TPS by fiscal year, respectively. These graphs indicate that the three loss rate models provide reasonable forecasts of the observed loss rates for each type. The volume-weighted mean absolute errors for REO, PFS, and TPS on the validation data are 0.0398, 0.0607, and 0.0409, respectively. They are 6.90%, 14.53%, and 8.29% of their respective mean loss severity rates, indicating small model prediction errors for both REO and TPS. The prediction error is slightly higher but acceptable for PFS, largely attributed to lack of sufficient data. Additionally, Exhibits D-13 to D-15 show that the model performance is superior in the periods with large data observations and the prediction error generally increases in those periods with less data, further confirming that data availability can reduce the overall prediction errors.

Exhibit D-13: Actual and Predicted REO Loss Severity Rates by Fiscal Year

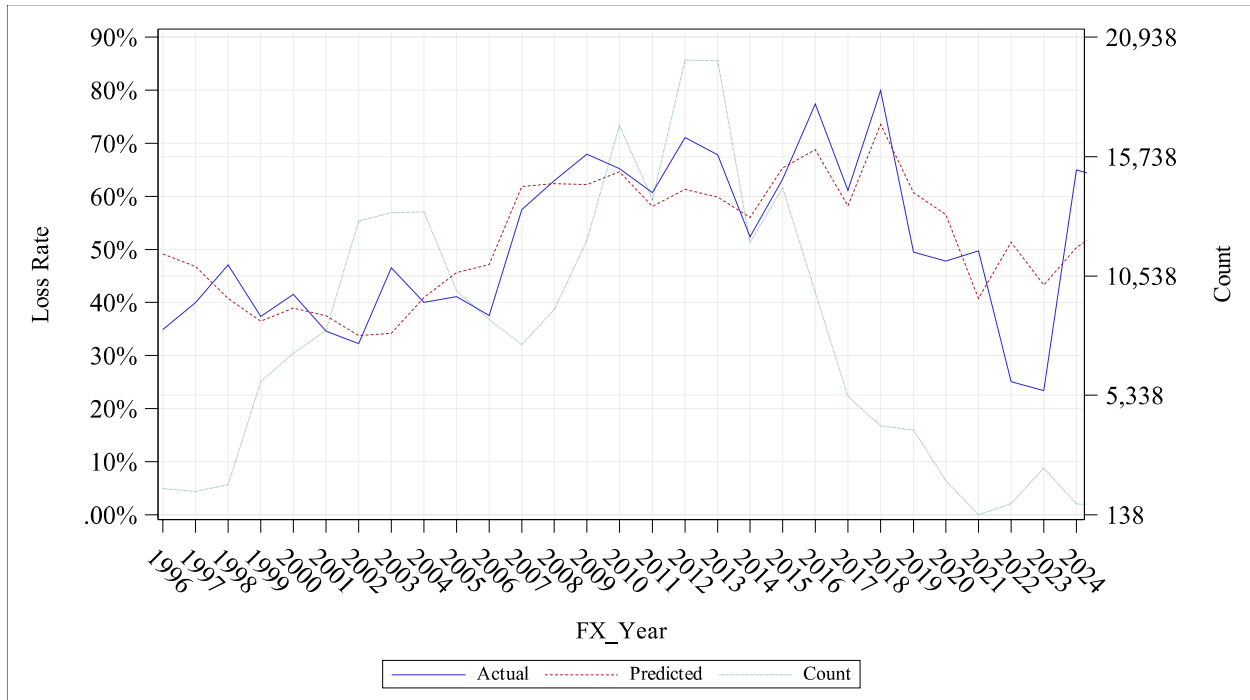
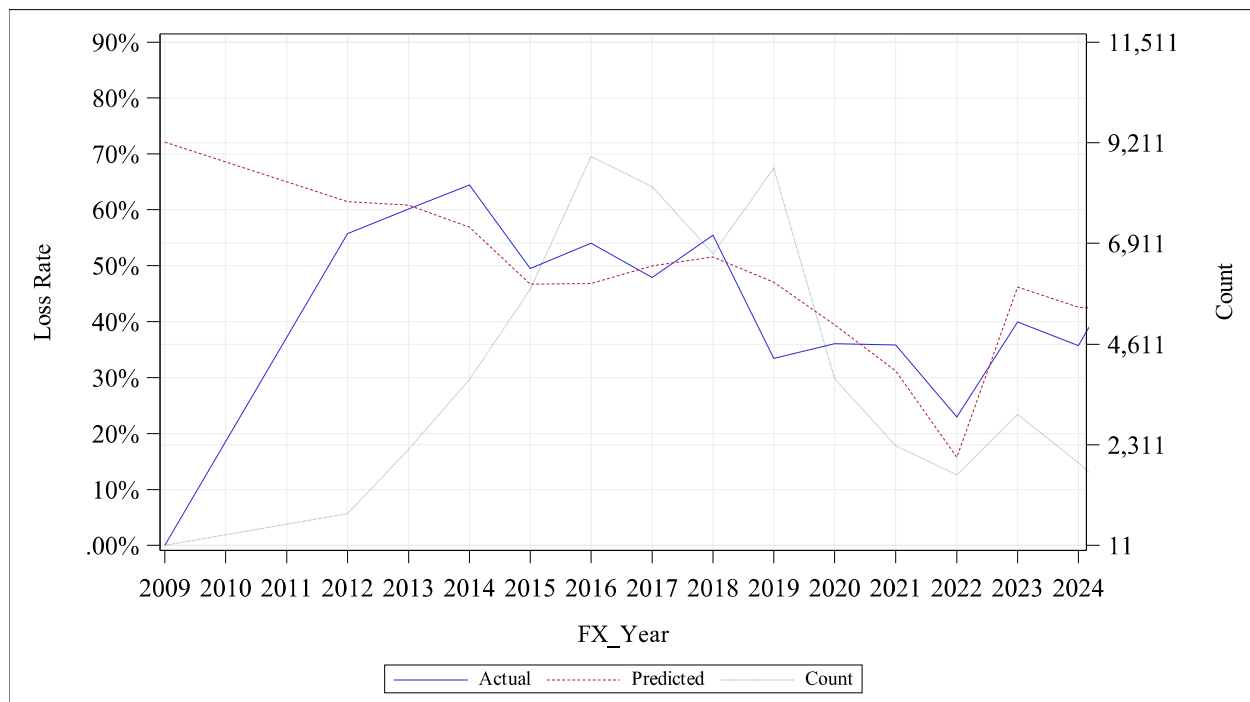




Exhibit D-14: Actual and Predicted PFS Loss Severity Rates by Fiscal Year



Exhibit D-15: Actual and Predicted TPS Loss Severity Rates by Fiscal Year

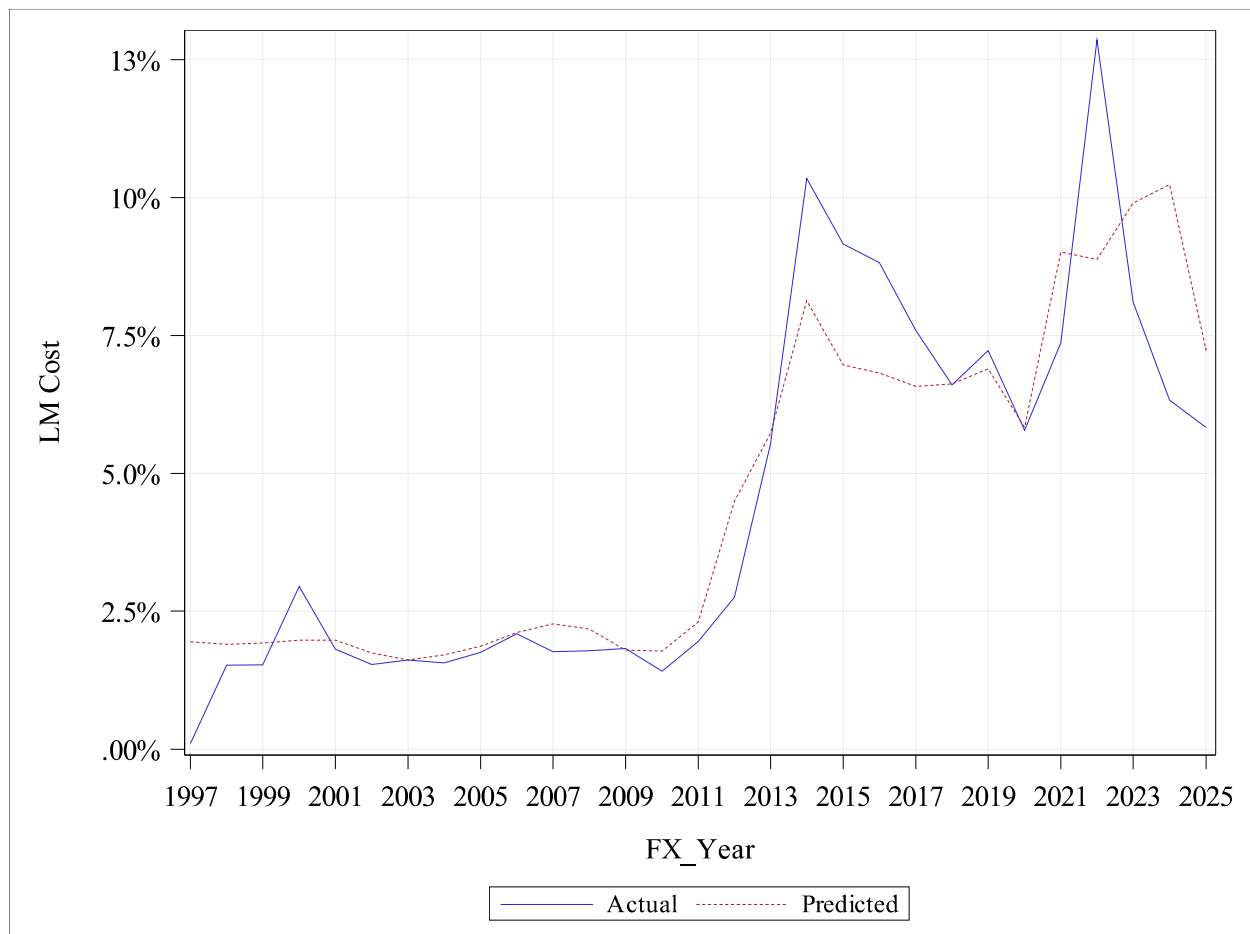


### D3.3.3 Loss Mitigation

The loss mitigation expense samples were equally split into an estimation sample and a holdout sample. The loss mitigation model was applied to generate predictions for the holdout sample, which were compared to the actual loss mitigation expense rates.

Exhibit D-16 compares the estimated and actual percentage loss mitigation expenses by fiscal year for the validation dataset. The volume-weighted mean absolute error of the loss mitigation model on the validation dataset is 0.0053, which is 10.78% of the mean loss mitigation rate, indicating a small model error. Overall, the loss mitigation model effectively captured loss mitigation policy regime changes and properly predicted the loss mitigation expenses across years.

Exhibit D-16: Estimated and Actual Percentage Loss Mitigation Expenses by Fiscal Year



## D4. Extension of Cash Flows Up to 40 Years

In our baseline model, we do not specifically incorporate loan extensions beyond 30 years. A research experiment is further performed to examine the impact of extended loans' cash flows on NPV. To do so, we first identify the proportion of extended loans using the loan maturity curves based on the full loan samples. In addition to the 30-year cash flow forecasting in our baseline model, we forecast another 10-year cash flows for extended loans using our existing transition, claims and loss mitigation models so that the total forecasting period becomes 40 years.

In extending cash flows beyond 30 years, we see that the NPV trend across cohort years generally follows the direction of projected performance in our baseline model. We find significantly enlarged net losses for earlier cohorts (1996-2012), while larger profits are observed for more recent cohorts (2013-2025). This could be related to the fact that the MIPs for loans originated from mid-2013 and onwards are mostly to be paid premiums for the entire life of the loan, while prior loans, particularly those originated between 2001 and 2012, only pay MIPs until their LTV falls to 78%. The expected premium income for the earlier cohorts in the extended years is significantly less than their expected costs.

Based on our analysis, the overall impact of incorporating loan extensions on NPV is less than a 1% change. This result appears to be heavily weighted in earlier cohorts as opposed to more recent cohorts. First, the extended cash flows for earlier cohorts are less discounted, compared to the cash flows of later cohorts (which occur in much later years). Second, the proportion of extended loans in earlier cohorts are significantly larger. For cohorts 1996 – 2012, approximately 30% of active loans have extended periods beyond 30 years, while for cohorts 2013 – 2025, less than 10% of active loans have extended periods beyond 30 years.

It is important to note that the above analysis only considers active loans with extended maturity and does not project future loan modification extensions for active loans. We also do not separately estimate the loan transition probabilities and claim rates for loans with extended maturity. We leave these as future research.

## Appendix E. Stochastic Simulation Models

This Appendix describes the stochastic models used to generate economic variables used in the Monte Carlo simulations of the FHA Single-Family Forward Mortgages Actuarial Review 2025. Based on the best fitted stochastic model, we use Monte Carlo simulation technique to simulate 1000 paths of future economic variables and obtain the 1<sup>st</sup>, 10<sup>th</sup>, 25<sup>th</sup>, 50<sup>th</sup>, 75<sup>th</sup>, 90<sup>th</sup> and 99<sup>th</sup> percentiles of the simulated paths.

This year's review updates the simulation models used in 2024 Review to obtain percentile paths. Each quarterly point of a percentile path is the percentile value across all simulation paths at that quarter used as the percentile reference path. Whichever real simulated path that is closest to the percentile reference path is identified as the obtained percentile path. This method uses the real simulated trajectory and represents the overall percentile profile among all the simulated paths. At the same time, in our Monte Carlo simulation, the simulated paths are centered on the baseline economic assumptions, this is, the 50<sup>th</sup> percentile of the simulated path is close to the baseline PEA and replaced by the PEA baseline assumption.

The estimated simulation models are identical for the Single-Family Forward Mortgages and HECM with respect to Treasury rates, SOFRs, and national and regional HPIs. Additional forecast models for 30-year mortgage rates and unemployment rates are applied to Single-Family Forward mortgages.

The simulated scenarios of the U.S. economic economy used as the components of the forecast include:

- 1-year CMT rate,
- 10-year CMT rate,
- 1-month Secured Overnight Financing Rate (SOFR), and
- 30-year fixed mortgage rate,
- Unemployment rate,
- FHFA national Purchase Only house price appreciation rate (HPI-PO).

The stochastic models are calibrated to historic data and are chosen based on augmented Dickey–Fuller test (ADF) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test for stationarity in time series; Box-Ljung (BL) for autocorrelation in residuals after model fitting; likelihood, AIC, and BIC values for parameter selection; and one-step rollover forecast test. At the same time, since all status transition probabilities are estimated and projected using a series of historically observed and projected interest rates with different maturity terms, the stochastic interest rate models are internally consistent in model calibration and forecasting. This approach is appropriate for the Actuarial Review as we are computing the present value of projected future cash flows for liability valuation.

## E1. Historical Data

### E1.1. Interest Rates

With the high inflation rate caused by the global oil crisis in the late 1970's, interest rates rose to a historically high level in the early 1980's. Then the Federal Reserve shifted its monetary policy from managing interest rates to managing the money supply, at least until inflation, and consequently interest rates receded. Exhibit E-1 shows historical 1-year and 10-year CMT rates from 1970 Q1 to 2025 Q2. The one-year Treasury rate (CMT1) fluctuated around 6% in the early 1970s and increased steadily to its peak of 16.31% in CY 1981 Q3. After that, it followed a decreasing trend and reached an all-time low around 1.2% in 2004. From then on, rates started a slow upward trend until the 2007 financial crisis and rates started a sharp downward trend reaching a historic low of 0.06% in CY 2021 Q2. Inflation turned up dramatically because of the COVID-19 pandemic. Monetary policy initiatives aimed to overturn the post-pandemic inflation, and we saw the Federal Reserve tightening where the one-year rate has been increasing up to 5.39% in 2023 Q3 and then turning down. The one-year CMT rate is 3.88% in 2025 Q3.

The ten-year Treasury rate (CMT10) generally followed a similar long-run pattern, though with less volatility. It rose from around 7% in the early 1970s to a peak of nearly 15% in 1981 and then declined steadily over the next four decades. By 2020–2021, the 10-year CMT fell below 1% in 2020 before rising alongside post-pandemic. As inflation accelerated in the post-pandemic period, long-term rates moved upward again, reaching about 4.45% in 2024 Q2 before easing slightly. The ten-year CMT rate is 4.26% in 2025 Q3.

Also shown in Exhibit E-1 is the 1-year SOFRs curve. Historical SOFRs data dated back to 2006 Q1. The SOFRs reflect Treasury-backed short-term funding costs and is closely tied to Federal Reserve policy, showing a similar cyclical pattern to the 1-year CMT but with smaller term premium. In the mid-2000s, 1-year SOFR peaked near 5.4%, fell to near 0.1% during the zero-interest-rate era, and then climbed to around 2.5%–2.7% during the 2018–2019 tightening cycle. Pandemic relief drove SOFR to record lows of 0.04–0.11% in 2020–2021 before it surged alongside policy rates, reaching 5.38% in 2023Q3. By 2025Q3, it had reduced to 3.81%, maintaining a tight alignment with the 1-year CMT.

Exhibit E-1 Historical Interest Rate

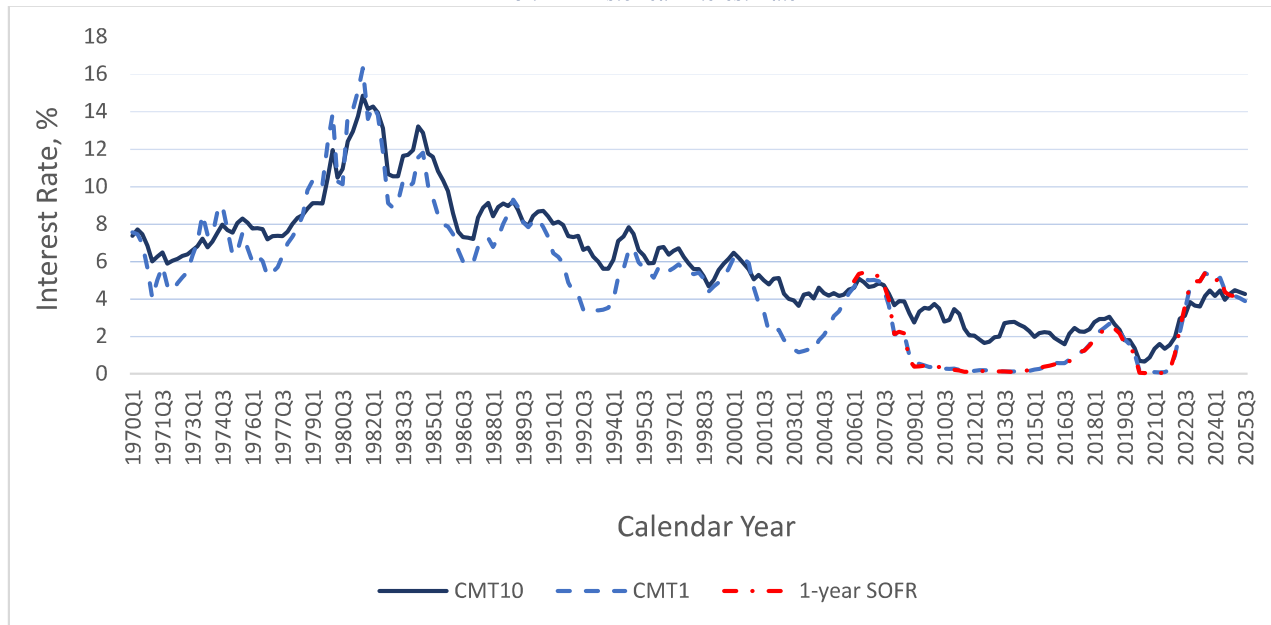


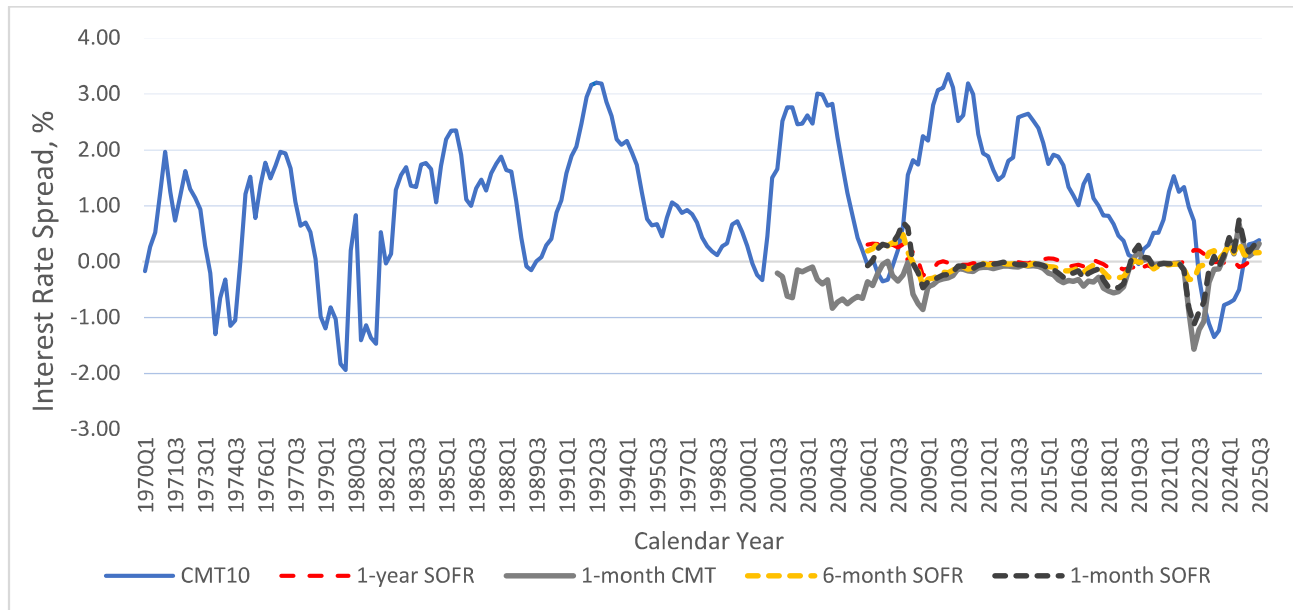
Exhibit E-2 shows historical interest rate spreads for the 10-year CMT, 1-month CMT, and SOFR tenors (1-year, 6-month, 1-month). The spread between the 10-year and 1-year Treasury rates appears to have above and below zero cycles and high volatilities. Historically, the spread has turned negative (yield curve inversion) before recessions, for example, in the late 1970s, early 1980s, 2000, 2006–2007, and again in 2022–2023. The most recent inversion, with the spread reaching  $-1.35\%$  in 2023 Q2. By 2025 Q3, the spread normalized to a positive  $0.38\%$ , suggesting some easing in monetary policy and reduced recession concerns.

The spread between 1-month CMT rate and 1-year CMT rate is typically negative ( $-0.1$  to  $-1.5$ ) having liquidity premium price incorporated. Episodes when the spread narrowed toward zero or briefly turned positive during the late 1970s–early 1980s, mid-2000s, and 2022–2023 correspond to aggressive Federal Reserve rate hikes. During easing cycles and crisis periods, including the early 1990s, post-2008, and pandemic years, the spread widened.

SOFRs are tied to secured funding markets and policy expectations, and their over 1-year CMT rate fluctuates around zero with much smaller variation than Treasury spreads at comparable maturities. The ARMA-GARCH models are identified for 1-year CMT rate and interest rate spreads.



Exhibit E-2 Historical Interest Rate Spread (%) with the 1-Year CMT



## E1.2. House Price Appreciation Rates

The national house price appreciation rate (HPA) is derived from the FHFA repeat sales seasonally adjusted purchase-only (PO) house price indices (HPIs). The PO HPI is used for national HPA simulation as it provides a reliable measure of housing market conditions since it is based on repeat sales at market prices and does not use any appraised values. The All Transaction (AT) version of HPI is used for deriving geographic dispersion factors as it retains significantly broader regional coverage. At the national level, the AT HPI is very close to the PO HPI.

The HPA at time  $t$  is defined as:

$$HPA_t = \frac{HPI_t}{HPI_{t-1}} - 1$$

Exhibit E-3 shows the quarterly national HPI and HPA from CY 1991 Q1 to CY 2025 Q2. The long-term average quarterly HPA is around 1.085% (4.41% annual rate). The HPI increased steadily before 2004 with an annual appreciation rate of about 4.64%. Then house prices rose sharply starting in 2004. The house price appreciation rate was around 10% annually during the subprime mortgage expansion period from 2004 to 2005 and reached its peak at an annual rate of 11.2 % in the second quarter of CY 2005. The house price appreciation slowed down in 2006. The overturn started in the second quarter of 2007 and the average growth rate of house prices became negative in 2011. Since then, house price appreciation has stabilized for 10 years. During COVID-19 pandemic period of 2020 to 2022, house prices increased at a much higher appreciation rate due to the economic stimulation policy and then slowed down after the pandemic was over. House appreciation rate started upward in the third quarter of 2020 and reached 19.45% in the second

quarter of 2021. House appreciation slowed down in 2022, dropping to an average annual rate of 8.45% and continued to drop to an average annual rate of 6.50% in 2023, 4.56% in 2024, and -1.06% in 2025 Q3. Exhibit E-4 shows the average quarterly HPA by selected historical time periods.

Exhibit E-3 Historical National HPI and Annualized HPA

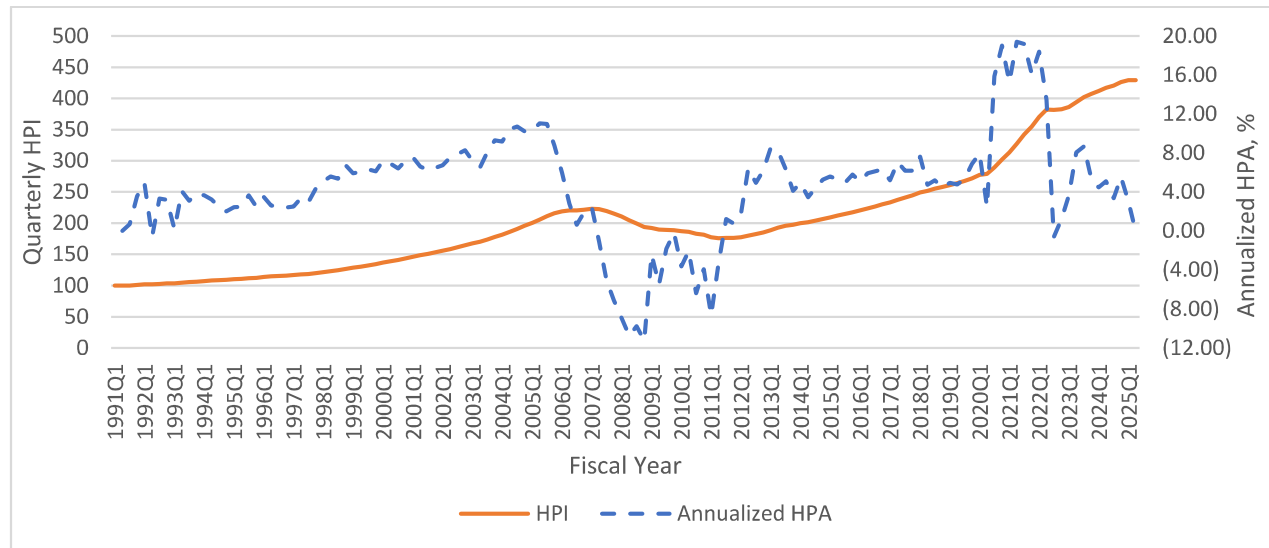


Exhibit E-4 Average Quarterly HPA by Time Span (Need to Update)

| Period            | Average Annual HPA |
|-------------------|--------------------|
| 1991 – 2003       | 4.64%              |
| 2004 – 2006       | 7.69%              |
| 2007 – 2011       | -4.87%             |
| 2011 – 2020 Q2    | 5.26%              |
| 2020 Q3 – 2022 Q2 | 14.75%             |
| 2022 Q3 – 2025 Q3 | 3.82%              |

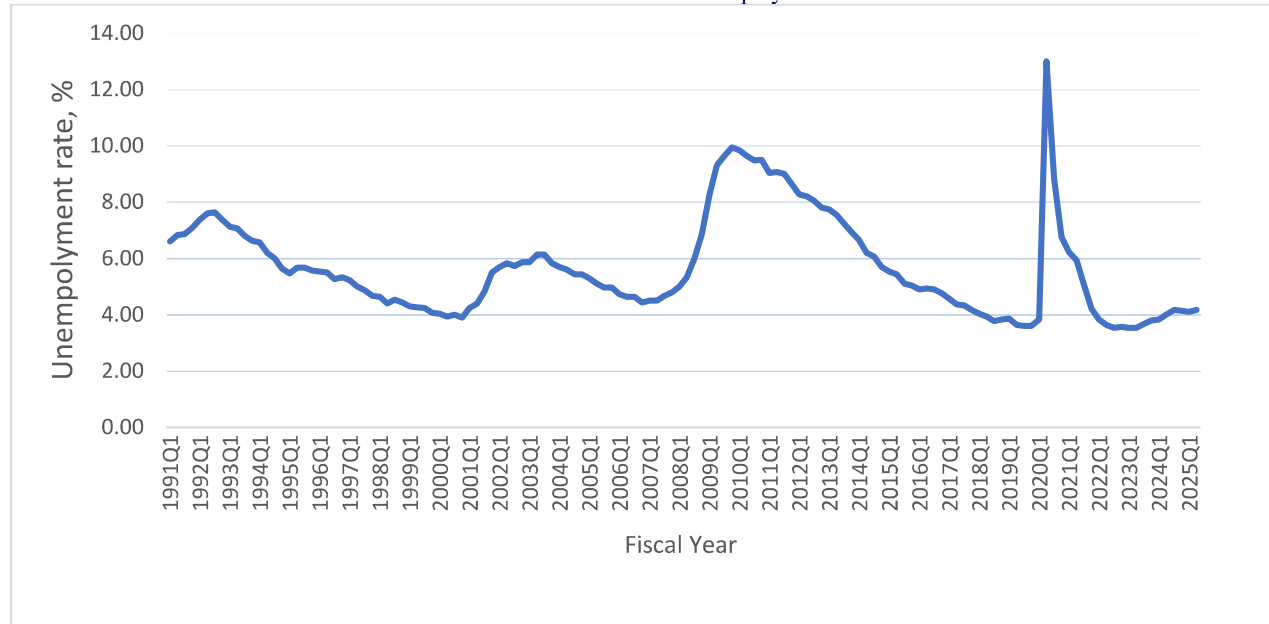
### E1.3. Unemployment Rates

Unemployment rates typically increase during economic downturns and decrease during economic growth periods. Government policies also significantly impact employment. Exhibit E-5 displays historical national unemployment rates since 1991Q1.

A period of robust job creation in late 1990s brought unemployment steadily down, reaching historically low levels below 4% by 2000Q4, fueled by the technology boom. The dot-com crash and 9/11 shock pushed unemployment above 6% by 2003 and fell to the mid-4% range by 2006–2007. The global financial crisis drove it sharply higher, peaking at nearly 10% in 2009–2010. Economy recovery brought a long steady economic expansion and reduced unemployment to 3.6% by late 2019. The pandemic triggered an unprecedented spike to 13% in 2020Q2, as the enforced lockdowns leading to widespread business closures and disruptions. Aggressive fiscal and

monetary policy, for example, Coronavirus Aid, Relief, and Economic Security Act (CARES Act), provided the largest economic stimulus in the U.S. history and brought down the unemployment rates back below 4% by early 2022 and stay below 4% till 2024 Q1. Since 2024 Q1 unemployment has drifted up only slightly. Overall, structural resilience in the U.S. labor market, along with policy interventions, has consistently brought unemployment back toward a long-run average of 4 to 5%

Exhibit E-5 Historical National Unemployment Rates



## E2. Stochastic Models and the Simulated Scenarios

Economic variables, either monetary policy-driven or credit conditions driven, exhibit high jumps in volatility around regime shift. Stochastic models need to account for heteroscedastic volatilities in these economic indicators caused by high economic instability and uncertainty.

For these reasons an Autoregressive Moving Average (ARMA) - General Autoregressive Conditional Heteroscedasticity (GARCH) modeling is chosen for each economic variable. ARMA-GARCH models combine two types of time series models: Autoregressive Moving Average (ARMA) models for the mean and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models for the variance. This approach is used when dealing with time series data that exhibits both autocorrelation (dependence of a value on its past values) and volatility clustering (periods of high volatility followed by periods of low volatility).

Stationarity is very important in forecasting. It enables the use of simpler and more accurate models to provide a solid foundation for forecasting future values. Non-stationary data, on the other hand, can lead to misleading results and inaccurate predictions because its statistical properties change over time, making it difficult to identify true trends and patterns. Therefore, ADF and KPSS) test

for stationarity were performed on all variables before specifying GARCH candidate models for the velocities.

BL tests are performed to the residuals of candidate models to identify the presence of autocorrelation (serial correlation) in the residuals of a fitted model. It assesses the overall autocorrelation up to a specified lag, rather than individual lags, to identify the best model. The following is the detailed description of the chosen univariate ARMA-GARCH model for each economic variable:

### 2.1. 1-Year Treasury Rate

Several Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are tested using historical 1-year CMT rates from fiscal year 1991 Q1 to CY 2025 Q2. Based on the AIC, BIC, and Likelihood values, the best fitted model is an AR(2)- GARCH(1,1) with student's t-distribution innovations and external regressor for conditional volatility.

Let  $r_{1,t}$  be the one-year Treasury rate at time  $t$ . The stochastic process takes the following form:

$$\Delta r_{1,t} = \sum_{i=1}^3 a_{1,i} \Delta r_{1,t-i} + \sum_{i=1}^5 b_{1,i} e_{1,t-i} + \varepsilon_t$$

where  $\varepsilon_t = \sigma_t z_t$ .  $z_t = \sqrt{\frac{v-2}{v}} T_v$ , where  $T_v$  follows a student's distribution with degrees of freedom  $v > 2$ , and variance  $\sigma_t^2$  follows a GARCH (1, 1) model,

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

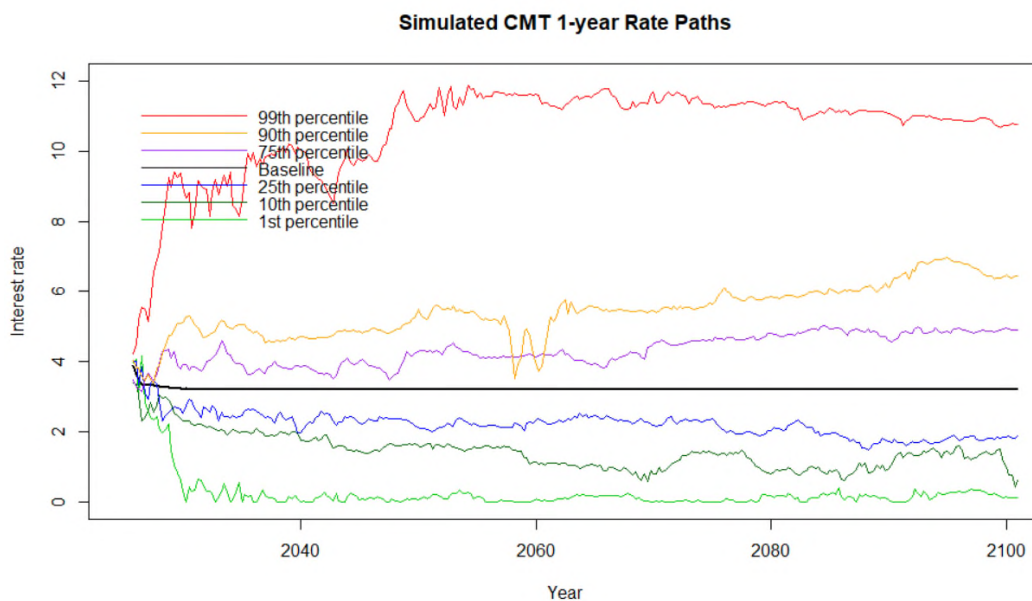
The estimated results are presented in Exhibit E-6.

Exhibit E-6 Estimation Results for 1-Year Rate Model

| Parameter | Estimate | Std. Error | t value  | Pr(> t ) |
|-----------|----------|------------|----------|----------|
| $a_{1,1}$ | 0.803108 | 0.176112   | 4.56022  | 0.000005 |
| $a_{1,2}$ | 0.579228 | 0.184815   | 3.13409  | 0.001724 |
| $a_{1,3}$ | -0.49987 | 0.128146   | -3.90076 | 0.000096 |
| $b_{1,1}$ | -0.26406 | 0.185094   | -1.42663 | 0.153686 |
| $b_{1,2}$ | -0.9273  | 0.158987   | -5.83256 | 0        |
| $b_{1,3}$ | 0.401383 | 0.122984   | 3.26371  | 0.0011   |
| $b_{1,4}$ | 0.260129 | 0.100466   | 2.58922  | 0.009619 |
| $b_{1,5}$ | -0.23893 | 0.089023   | -2.68393 | 0.007276 |
| $\omega$  | 0.000461 | 0.000525   | 0.87677  | 0.380609 |
| $\alpha$  | 0.321652 | 0.064511   | 4.98597  | 0.000001 |
| $\beta$   | 0.677348 | 0.046941   | 14.42966 | 0.000001 |
| $v$       | 5.422451 | 1.199048   | 4.5223   | 0.000001 |

The model based on these parameters is used to simulate the one-year Treasury rates for the forecast period starting in FY 2025 Q3. When the simulation is implemented, the conditional mean is replaced by the PEA baseline forecast. This simulation method is to ensure the stochastic path of future 1-year Treasury rate is centered on the PEA baseline forecast. We applied the same procedure for the conditional mean in the 10-year Treasury rate, SOFR and HPA rate.

1000 paths of the future 75 years<sup>80</sup> of 1-year Treasury rates are simulated. The 1<sup>st</sup>, 10<sup>th</sup>, 25<sup>th</sup>, 75<sup>th</sup>, 90<sup>th</sup>, and 99<sup>th</sup> percentiles<sup>81</sup> paths are displayed. The 50<sup>th</sup> percentile path is close to the baseline forecast and replaced by the PEA baseline assumption. The resulting forecasts for the one-year Treasury rates are shown in the following chart for the baseline PEA and the four alternative stochastic percentile paths.



## E2.2. 10-Year Treasury Rate

The 10-year Treasury rate is modeled by adding a stochastic spread term to the simulated 1-year Treasury rate. We estimate the dynamics of the spread between the 10-year Treasury rate and 1-year Treasury rate from historical data.

The best model is chosen based on stationarity test, Ljung-Box test on standardized residuals, and Ljung-Box test on standardized squared residuals, together with the AIC, BIC, and likelihood values, the best fitted GARCH model is ARMA(2, 2) - GARCH(1,1).

Let  $s_{10,t}$  be the spread between the 10-year and one-year Treasury rates at time  $t$ . Mathematically, the model for  $s_{10,t}$  is as follows.

<sup>80</sup> The number of projection years is 50 in 2025 Actuarial Review.

<sup>81</sup> The 1<sup>st</sup> and 99<sup>th</sup> percentiles of all variables are displayed for reference, not included in computing the NPV.

$$s_{10,t} = a_{10,0} + \sum_{i=1}^2 a_{10,i} s_{10,t-i} + \sum_{i=1}^2 b_{10,i} e_{1,t-i}$$

where  $\varepsilon_t$  is a normal innovation with mean 0 and variance  $\sigma_t^2$  following a GARCH (1, 1) model,

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

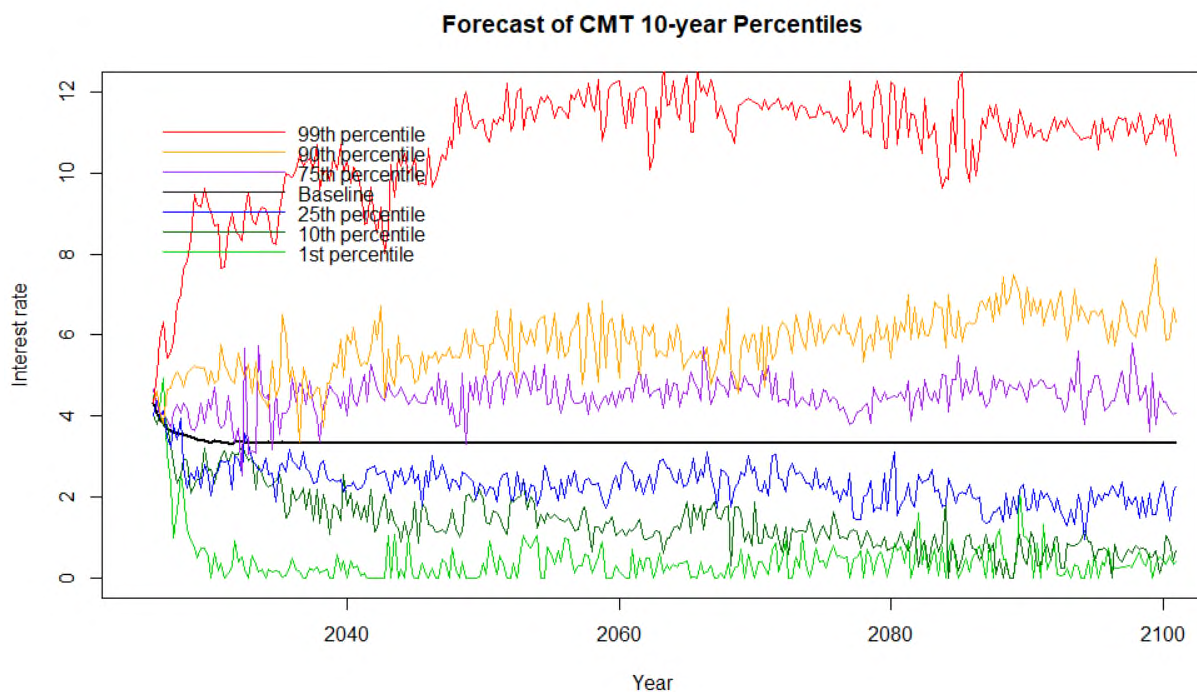
The model is estimated based on historic spread data from CY 1970 Q1 to CY 2025Q2. parameters are shown in the following Exhibit E-7.

Exhibit E-7 Estimation Results for 10-Year Rate Spread Model

|            | Estimate | Std. Error | t value | Pr(> t ) |
|------------|----------|------------|---------|----------|
| $a_{10,0}$ | 0.770408 | 0.242655   | 3.1749  | 0.001499 |
| $a_{10,1}$ | 1.62748  | 0.103137   | 15.7798 | 0        |
| $a_{10,2}$ | -0.68056 | 0.096812   | -7.0297 | 0        |
| $b_{10,1}$ | -0.28468 | 0.136712   | -2.0823 | 0.037314 |
| $b_{10,2}$ | -0.11635 | 0.086099   | -1.3514 | 0.176578 |
| $\omega$   | 0.009441 | 0.005299   | 1.7818  | 0.07479  |
| $\alpha$   | 0.221746 | 0.076849   | 2.8855  | 0.003908 |
| $\beta$    | 0.736279 | 0.075965   | 9.6924  | 0        |

We used the estimated parameters to simulate the spread between the 10-year and 1-year Treasury rates with the conditional mean equal to the PEA baseline forecast, such that the 1000 simulated paths are centered on the baseline estimation. The simulated spread percentile paths are added to the corresponding 1-year CMT percentile paths. Percentile paths are obtained therein. The 1<sup>st</sup>, 10<sup>th</sup>, 25<sup>th</sup>, 75<sup>th</sup>, 90<sup>th</sup>, and 99<sup>th</sup> percentiles paths, together with the PEA baseline assumption for the ten-year Treasury rates are shown in the following chart.





### E2.3 1-Month SOFR

The first order of difference is taken to ensure stationarity in time series. Let  $\Delta s_{s1,t}$  be the first order of difference of the spread between the 1-Month SOFR and 1-year CMT rates at time  $t$  and  $r_{1,t}$  1-year CMT rate at time  $t$ , the best fitted model for 1-Month SOFR spread rate is an AR(1)-GARCH (1,1) model with Student's distribution innovations:

$$\Delta s_{s1,t} = \alpha_{s1,1} \Delta s_{s1,t-1} + \varepsilon_{s1,t}$$

where  $\varepsilon_{s1,t} = \sigma_t z_t$  and innovations  $z_t = \sqrt{\frac{v-2}{v}} T_v$ , where  $T_v$  follows a student's distribution and variance  $\sigma_t^2$  follows a GARCH (1, 1) model,

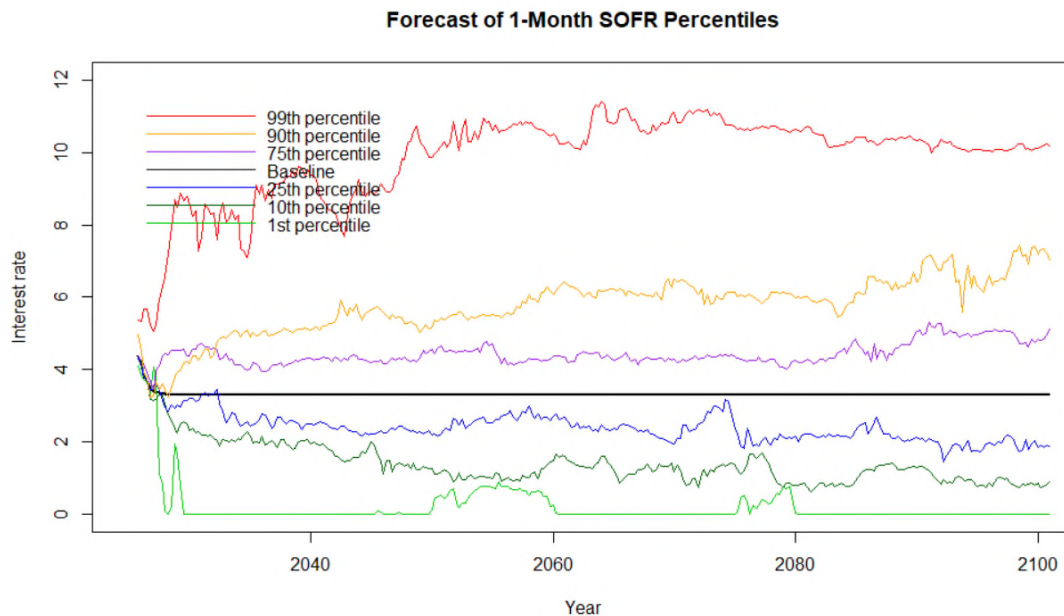
$$\sigma_t^2 = \omega + \alpha \varepsilon_{s1,t-1}^2 + \beta \sigma_{t-1}^2$$

Moody's historical 1-Month SOFRs dated back to 2006 Q1. The best fitted GARCH model is chosen based on Ljung-Box test on standardized residuals, Ljung-Box test on standardized squared residuals, the AIC, BIC, and likelihood values. The estimated parameters are shown in Exhibit E-8.

Exhibit E-8 Estimation Results for the 1-Month SOFR Spread Model

|                 | Estimate | Std. Error | t value | Pr(> t ) |
|-----------------|----------|------------|---------|----------|
| $\alpha_{s1,1}$ | 0.189847 | 0.120215   | 1.5792  | 0.114285 |
| $\omega$        | 0.000688 | 0.000954   | 0.7215  | 0.470605 |
| $\alpha$        | 0.434875 | 0.163349   | 2.6622  | 0.007762 |
| $\beta$         | 0.564125 | 0.170833   | 3.3022  | 0.000959 |
| $\nu$           | 3.599493 | 0.818116   | 4.3997  | 0.000011 |

We used the estimated parameters to simulate the 1-Month SOFR spread rate with the conditional mean equal to the baseline spread. The simulated spread percentile paths are added to the simulated 1-year CMT percentile paths. The 1-Month SOFR percentile paths are obtained therein as shown in the following chart.



#### E2.4 30-Year Fixed Rate Mortgage (FRM)

Based on the ADF and KPSS tests for stationarity, a GARCH model is used to model the spread between fixed 30-year mortgage rate and 1-year CMT rate. The best fitted GARCH model is chosen based on Ljung-Box test on standardized residuals, Ljung-Box test on standardized squared residuals, the AIC, BIC, and likelihood values. Let  $s_{m,t}$  be the spread between 30-year mortgage rate and 1-year CMT rate. The spread is modeled by ARMA (2, 3)-GARCH ((1,1)). Mathematically put,

$$s_{m,t} = a_{m,0} + \sum_{i=1}^2 a_{m,i} s_{1,t-i} + \sum_{i=1}^3 b_{m,i} e_{1,t-i} + \varepsilon_t$$

where  $\varepsilon_{m,t}$  is a skewed t-distributed innovation with variance  $\sigma_t^2$  following a GARCH (1, 1) model,

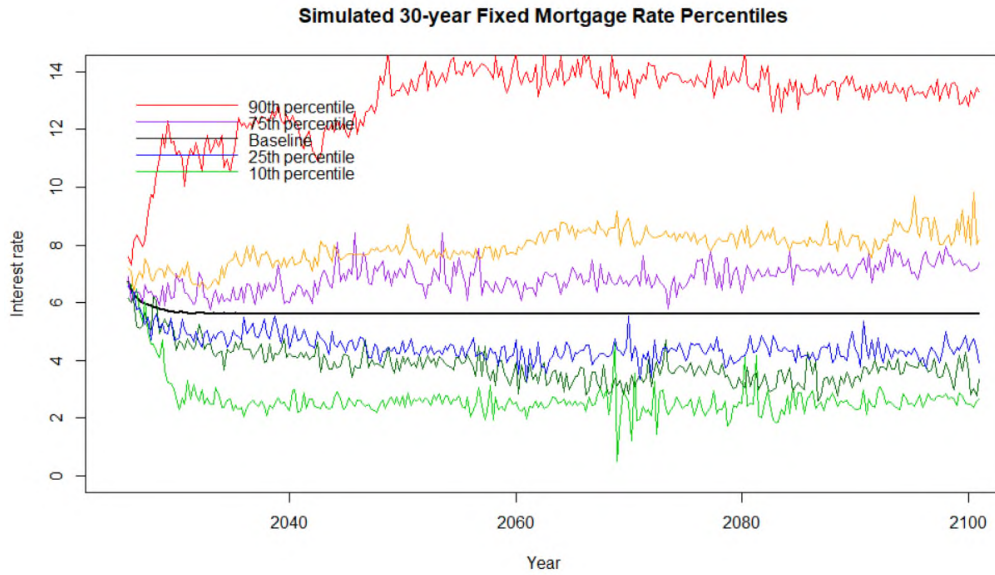
$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

Using historical fixed 30-year mortgage rates from 1971Q2 to 2025Q2 from Moody's, the estimated results are presented in Exhibit E-9.

Exhibit E-9 Estimation Results for 30-Year Mortgage Rate Model

| Parameter | Estimate | Std. Error | t value  | Pr(> t ) |
|-----------|----------|------------|----------|----------|
| $a_{m,0}$ | 2.731439 | 0.195927   | 13.9411  | 0        |
| $a_{m,1}$ | 1.776795 | 0.030792   | 57.704   | 0        |
| $a_{m,2}$ | -0.81161 | 0.029974   | -27.0768 | 0        |
| $b_{m,1}$ | -0.57887 | 0.072021   | -8.0375  | 0        |
| $b_{m,2}$ | -0.1544  | 0.068168   | -2.2649  | 0.023516 |
| $b_{m,3}$ | 0.123223 | 0.065839   | 1.8716   | 0.061265 |
| $\omega$  | 0.009108 | 0.006108   | 1.4912   | 0.135909 |
| $\alpha$  | 0.202221 | 0.122672   | 1.6485   | 0.099259 |
| $\beta$   | 0.757155 | 0.111515   | 6.7897   | 0        |
| Skew      | 1.280055 | 0.122467   | 10.4522  | 0        |
| Shape     | 4.670849 | 1.315986   | 3.5493   | 0.000386 |

We used the estimated parameters to simulate 30-year mortgage rate spread rate with the conditional mean equal to the baseline spread. The simulated spread percentile paths are added to the simulated 1-year CMT percentile paths. The 30-year mortgage rate percentile paths are obtained therein as shown in the following chart.



## E 2.5 Unemployment Rate (UE)

### E 2.5.1. National Unemployment Rate

The Covid-19 pandemic disproportionately impacted service-based industries where work was typically in-person. The high unemployment rate was unprecedented in its speed and scale, leading to 13% in 2020Q2, the highest rate since the Great Depression. In the model estimation, this one-time jump in the unemployment rate was treated as an outlier and smoothed out using the moving average of the data.

Based on the ADF and KPSS tests for stationarity, the first order of difference is taken to ensure a stationary time series for use. Let  $\Delta ue_t$  be the first order of difference of the unemployment rates. The best fitted model to  $\Delta ue_t$  is

$$\Delta ue_t = a_{u,1} \Delta ue_{t-1} + b_{u,1} e_{1,t-1} + \varepsilon_{ue,t},$$

and  $\varepsilon_{ue,t}$  is a skewed t-distributed innovation with variance  $\sigma_t^2$  following a GARCH (1, 1) model,

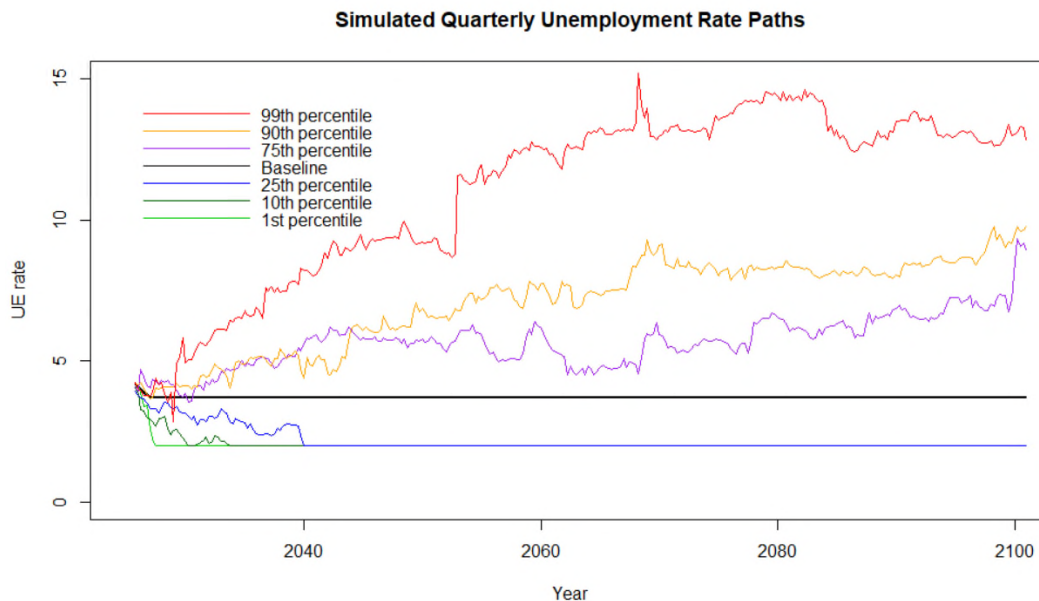
$$\sigma_t^2 = \omega + \alpha \varepsilon_{ue,t-1}^2 + \beta \sigma_{t-1}^2,$$

Using the historic data from 1970Q1 to 2025Q2, we estimate the model and have the results as shown in Exhibit E-10. The unemployment percentile paths are obtained as shown in the following chart.

Exhibit E-10 Estimation Results for the National UE Rate Model

|           | Estimate | Std. Error | t value  | Pr(> t ) |
|-----------|----------|------------|----------|----------|
| $a_{u,1}$ | 0.9834   | 0.004408   | 223.0985 | 0        |
| $b_{u,1}$ | 0.32015  | 0.083456   | 3.8361   | 0.000125 |
| $\omega$  | 0.03021  | 0.01577    | 1.9157   | 0.055402 |
| $\alpha$  | 0.49621  | 0.34458    | 1.44     | 0.149859 |
| $\beta$   | 0.23286  | 0.116171   | 2.0045   | 0.045021 |
| skew      | 1.08465  | 0.148916   | 7.2837   | 0        |
| shape     | 2.83346  | 0.613304   | 4.62     | 0.000004 |

We used the estimated parameters to simulate unemployment rates with the conditional mean equal to the baseline unemployment rates. A maximum of 20% and a minimum of 2% based on historical statistics are enforced to cap the simulated paths. The simulated percentile paths are obtained therein as shown in the following chart.



### E 2.5.2. Geographic Dispersion

Regional unemployment rate forecasts incorporate a geographic dispersion factor calculated from Moody's forecast of national and regional state- and MSA-level unemployment forecasts. Specifically, at each time  $t$ , the dispersion of unemployment rates between the  $i$ th region and the national forecast is calculated as follows:

$$Disp_{i,t}^{Base} = (UE_{Moody}_{i,t}^{Base} - UE_{Moody}_{national,t}^{Base})$$

This dispersion forecast under Moody's baseline estimates was preserved for all local unemployment forecasts under individual future economic paths. That is, for economic path  $j$ , the unemployment of the  $i$ th region at time  $t$  was computed as:

$$UE_{i,t}^j = (UE_{i,t}^j - DISP_{i,t}^{Base})$$

This approach retains the relationship between national and regional unemployment rates captured in the Moody's baseline forecast while preserving consistency with the national-level stochastic simulations.

## E2.6 House Price Appreciation Rates

### E2.6.1. National HPA

Several GARCH models are fitted to the historical house appreciation rates and its first order of difference and one-year rollover forecast test is conducted to evaluate the models. Based on the ADF and KPSS tests for stationarity and the forecast evaluation, the AR(2)-GARCH(1,1) model is recommended as the most statistically adequate and interpretable choice.

$$HPA_t = a_{h,1}HPA_{t-1} + a_{h,2}HPA_{t-1} + \varepsilon_{h,t}$$

where  $\varepsilon_{h,t}$  is a skewed t-distributed innovation with variance  $\sigma_t^2$  modelled by a GARCH (1, 1) model,

$$\sigma_t^2 = \omega + \alpha\varepsilon_{h,t-1}^2 + \beta\sigma_{t-1}^2$$

The GARCH (1,1) model with skewed t-distributed innovations performs much better than the one with normal innovations in this model. Using the historic data from 1991Q1 to 2025Q2, we estimate the model and have the results as shown in Exhibit E-11.

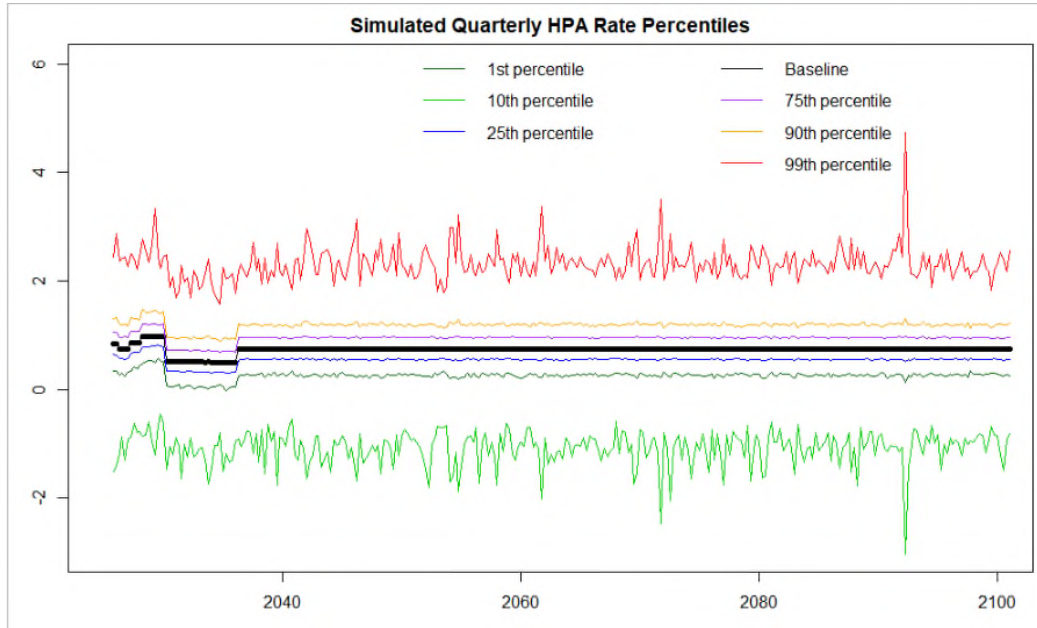
Exhibit E-11 Estimation Results for the National HPA Model

|           | Estimate | Std. Error | t value | Pr(> t ) |
|-----------|----------|------------|---------|----------|
| $a_{h,1}$ | 0.795566 | 0.071199   | 11.1739 | 0        |
| $a_{h,2}$ | 0.205915 | 0.073178   | 2.8139  | 0.004894 |
| $\omega$  | 0.019701 | 0.012255   | 1.6075  | 0.107935 |
| $\alpha$  | 0.462428 | 0.207614   | 2.2273  | 0.025924 |
| $\beta$   | 0.536572 | 0.163344   | 3.2849  | 0.00102  |
| skew      | 0.851692 | 0.085036   | 10.0157 | 0        |
| shape     | 4.421421 | 1.38624    | 3.1895  | 0.001425 |

We used the best fitted model to simulate 1000 future HPA paths starting from 2025 Q3, with the conditional mean equal to the PEA baseline forecast and obtain the 1<sup>st</sup>, 10<sup>th</sup>, 25<sup>th</sup>, 75<sup>th</sup>, 90<sup>th</sup>, and 99<sup>th</sup> percentile paths of the future quarterly HPA rates. Since the high volatility in HPA rates, the obtained percentile paths cross each other. Recall that the percentile path is identified to the simulated path who is closest to the quantile path, and the quantile path has every point being the



corresponding percentile among the simulated values in each individual quarter. To avoid the situation of crossing simulated percentile paths, we end up with setting the HPA percentile paths to be the ranked percentile of simulated HPA rates at each individual quarter, as shown in the following chart.



#### E2.6.2. Geographic Dispersion

The MSA-level HPA forecasts were based on Moody's forecast of local and the national HPA forecasts. Specifically, at each time  $t$ , there is a dispersion of HPAs between the  $i$ th MSA and the national forecast:

$$Disp_{i,t}^{Base} = (HPA_{i,t}^{Base} - HPA_{national,t}^{Base})$$

This dispersion forecast under Moody's baseline estimates was preserved for all local house price forecasts under individual future economic paths. That is, for economic path  $j$ , the HPA of the  $i$ th MSA at time  $t$  was computed as:

$$HPA_{i,t}^j = (HPA_{i,t}^j - DISP_{i,t}^{Base})$$

This approach retains the relative current housing market cycle among different geographic locations, and it allows us to capture the geographical concentration of FHA's current endorsement portfolio. This approach is also consistent with Moody's logic in creating local market HPA forecasts relative to the national HPA forecast under alternative economic scenario forecasts. We understand this approach is equivalent to assuming perfect correlation of dispersions among different locations across simulated national HPA paths, which creates systematic house price

decreases during economic downturns and vice versa during booms. Due to Jensen's Inequality, this tends to generate a more conservative estimate of claim losses.

### **E3. COVID-19 Pandemic Consideration**

The impact from the COVID-19 pandemic is noticeable and dramatic when analyzing these economic indicators, causing higher volatility in these economic variables. Abrupt changes in the recent historic data of these economic measures present additional challenges when fitting stochastic models. Because of the historic nature of this event and the changing economic environment before and after the pandemic, it is difficult to ascertain which impacts might be attributed solely to the pandemic, and whether these changes will persist in the future or revert to pre-pandemic conditions. Rather than apply different models including and excluding the pandemic period to interpret COVID-19 impacts, we use customized GARCH models for the individual economic variables to capture the high volatility of the COVID-19 period and subsequent economic changes in the data and to develop the simulated diversions from the PEA baseline assumptions.

With 2025 economic data, the best fitted GARCH models have similar structures to the corresponding models used in 2023 and 24 Actuarial Review, with slightly changed parameters based on model validation test results. This evidences that GARCH models can capture the volatilities in various economic variables, including the impact of COVID-19. Therefore, we continue to use this approach for the FY 2025 review.

## **Appendix F. Comparison of HUD and ITDC Models and Assessment of Vulnerabilities**

As part of the statutory actuarial review process, the results of review of HUD's Forward and HECM models will be provided as an addendum to this report following its official publication. This addendum will include supplemental documentation and analysis that were not available at the time of release but are necessary to provide enhanced transparency and completeness of the actuarial review. The addendum will be published promptly upon finalization and will be considered an integral component of the actuarial review for the 2025 fiscal year.

## **Appendix G. Tables of Historical and Projected Rates of Loan Termination and Loss Severity Rates**

Note: The relevant tables are provided in a separate file along with this document.

## **Appendix H. Logistic Model Estimation Results**

Note: The detailed results are provided in separate file attachments along with this document.